Marriage, Cohabitation, and Separation: A Dynamic Approach to the Second Demographic Transition

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Abstract

Across many advanced economies, the second demographic transition has reshaped household formation: marriage has declined, cohabitation has expanded, and both divorce and separation hazards have fallen. Using four decades of monthly U.S. demographic data, I first document three facts: (i) marriage has declined while cohabitation has risen, (ii) both unions have become more stable over time, and (iii) there are two inflection pointsthe mid-1990s, when substitution from marriage to cohabitation accelerated, and after the 2008 financial crisis, when remaining single became more common. Existing static or dynamic-stationary models cannot explain why fewer matches are formed even as those that do persist are more stable. To address this gap, I develop and estimate a dynamic, non-stationary marriage matching model with endogenous dissolution which allows for both marriage and cohabitation. The estimates show that rising match-formation costs outpaced surplus gains, reducing partnership formation, while marriage stability is driven by rising surplus and cohabitation stability by higher dissolution costs. Policy reforms in the 1990s coincide with the marriage-cohabitation substitution, and counterfactuals indicate that, coming out of the 2008 crisis, had house prices not risen so sharply, marriage formation would have been higher while cohabitation would have decreased.

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1 Introduction

Across many advanced economies, patterns of family formation have shifted dramatically over the past several decades (Lesthaeghe, 2020). Marriage has declined, cohabitation has become a widespread alternative, and both divorce and separation hazards have fallen from their historical peaks. Together, these developments are often described as the second demographic transition, reflecting a broad reconfiguration of how individuals form and sustain partnerships. There is extensive empirical evidence documenting these phenomena.[1] However, existing theoretical frameworks cannot fully rationalize them. Static models explain cross-sectional differences in who marries or cohabits but overlook the dynamics of how flows into and out of partnerships evolve over time. Dynamic approaches, while forward-looking, typically impose stationarity and treat separation as exogenous, leaving them unable to explain why fewer matches are forming even as those that do persist are more stable. Rationalizing these changes requires a framework that is dynamic, non-stationary, and capable of capturing endogenous dissolution as well as incorporating the distinction between marriage and cohabitation.

My paper asks: what economic forces underlie the second demographic transition—declining partnership formation alongside rising union stability—and to what extent these changes can be attributed to evolving match surplus and partnership costs, including those shaped by housing and asset constraints. The forces shaping household formation often work in opposing directions: rising match surplus should encourage more partnerships, but higher formation or dissolution costs may discourage them. To address this, I build a dynamic, non-stationary marriage matching model with endogenous dissolution and the possibility of both marriage and cohabitation. This framework extends the transferable-utility matching models of Choo and Siow (2006), Choo (2015), Mourifié and Siow (2021), and Ciscato (2024), while addressing the limitations of existing static or dynamic-stationary approaches that cannot capture evolving flows into and out of partnerships over time. The model enables me to decompose observed trends in household formation into the underlying economic components that drive them, quantifying the relative roles of changing surplus, formation costs, and dissolution costs in shaping the second demographic transition.

My first contribution is to document three facts about household formation during the second demographic transition. Using four decades of monthly U.S. data from the Current Population Survey (CPS), I show that (i) marriage rates have declined while cohabitation has risen, (ii) both marriage and cohabitation have become more stable over time, and (iii)

[1] See e.g., Lafortune et al. (2022), Lee (2015), Lundberg et al. (2016), Zaidi and Morgan (2017)

there are two clear inflection points in household formation patterns: the mid-1990s, when substitution from marriage to cohabitation accelerated, and the years following the 2008 financial crisis, when remaining single became increasingly common. To extend cohabitation measures consistently back before 2007, I reconstruct historical cohabitation status using a neural network trained on post-2007 data, allowing me to track transitions across the entire 1980–2023 period. These facts build on and extend the descriptive literature in demography and economics, such as Lesthaeghe (2010), Lundberg et al. (2016), and Lafortune et al. (2022), by showing that the retreat from marriage has been accompanied by greater partnership stability. These facts define the empirical regularities that my theoretical framework seeks to rationalize.

The second contribution I make is developing a dynamic, non-stationary marriage matching model with endogenous dissolution and the distinction between marriage and cohabitation. Unlike static frameworks that focus on cross-sectional stocks, or dynamic-stationary approaches that abstract from long-run calendar-time changes (Choo and Siow, 2006; Choo, 2015; Ciscato, 2024), my model captures the flows into and out of partnerships and allows for parameters to evolve over time. A key feature of the framework is its ability to separately identify match surplus, match-formation costs, and dissolution costs, thereby disentangling forces that can work in opposing directions. While prior work has often treated separation as exogenous or modeled it via match-quality shocks (Weiss and Willis, 1997; Bruze et al., 2015; Goussé et al., 2017; Chen and Choo, 2023), recent contributions incorporating endogenous separation (Ciscato, 2024; Reynoso, 2024) do not address the non-stationary case or separation costs. My framework extends these approaches by simultaneously incorporating non-stationarity, endogenous dissolution, and match-formation costs, allowing me to rationalize long-run shifts in household formation. Separately identifying these parameters is essential for understanding what drives observed changes: if matches are more stable, is this because surplus is higher or because dissolution costs are higher? Without this separation, we risk misattributing the source of observed stability.

My third contribution is to apply the model to shed new light on the drivers of household formation patterns and their heterogeneity. The estimates show that rising match-formation costs have outpaced gains in average match surplus, reducing overall partnership formation, while changes in per-period surplus and separation costs have contributed to increased match stability. However, this experience differs depending on whether we consider marriage or cohabitation. In the case of marriage, increased stability comes from rising per-period surplus. For cohabitation, it is a combination of falling surplus and rising dissolution costs. These parameters should be interpreted broadly: formation and dissolution costs encompass not

only financial or institutional barriers, but also evolving social and behavioural frictions that affect how individuals meet, form, and sustain relationships. For example, even if economic conditions remain constant, rising formation costs may reflect changes in social interaction patterns, preferences for independence, or cultural norms surrounding commitment.

The model also reveals that the returns to partnership have evolved unevenly across socioeconomic groups. Individuals with lower levels of education have experienced smaller gains in match surplus and larger increases in formation costs, reducing the likelihood of entering a union. These results are consistent with prior evidence on the unequal retreat from marriage across socioeconomic groups (Lundberg et al., 2016; Chambers et al., 2025). Two key episodes illustrate how these forces may operate. In the 1990s, changes in household formation coincide with policy reforms regarding paternity establishment for unmarried fathers, which altered the incentives surrounding marriage and cohabitation (Rossin-Slater, 2017). In the post-2008 period, rising housing prices and broader increases in the cost of living have been hypothesized to reduce partnership formation and increase the propensity to remain single (Cox and Stone, 2025). Housing provides a useful example for interpreting these dynamics: higher prices raise the cost of forming new partnerships but also discourage dissolution once a household is established, reflecting how cost-of-living and asset access influence both entry into and exit from relationships (Lafortune and Low, 2023).[2] My results thus provide structural evidence that these mechanisms—operating through both economic and behavioural channels—play a central role in the evolution of modern household formation.

Empirically, I estimate the model using four decades of monthly panel data from the Current Population Survey. Having established these mechanisms, I next estimate the model empirically using four decades of monthly panel data from the Current Population Survey. The data allow me to observe transitions between being single, married, and cohabiting, which I use to construct transition probabilities over time. These transition patterns provide the key moments for estimation: I match the observed probabilities to those implied by the model in order to recover time-varying parameters governing match surplus, formation costs, and dissolution costs. This structural estimation strategy takes advantage of the long-run, high-frequency nature of the CPS, which makes it possible to track gradual shifts in household formation and stability over the second demographic transition. My nonparametric estimators fit the data exactly and, in the spirit of Choo and Siow (2006), retain the tractability of closed-form expressions for model quantities. This equilibrium framework not only facilitates counterfactual analyses but also ensures that the model can be simulated without significant

[2]To address potential endogeneity between local housing costs and family-formation decisions, I exploit variation in rent control policies across metropolitan areas as an instrument for housing prices. The details of this IV strategy are presented in Section 5.

computational burden.

The model explains the central puzzle of the second demographic transition: declining partnership formation alongside rising match stability. The estimates show that average match surplus has risen over time, which encourages stability, but that increases in match-formation costs have outpaced these gains, leading to fewer partnerships overall. This effect is most pronounced among couples with lower levels of education; in particular, couples in which the woman has less than a college degree have experienced the largest change, providing structural context for the descriptive patterns recently documented by Chambers et al. (2025). The mechanisms also differ by partnership type: for cohabitation, rising dissolution costs have reinforced stability once unions are formed, while for marriage, increased stability is driven more directly by rising surplus. This decomposition clarifies why household formation has retreated even as existing unions endure, a pattern that static or stationary models cannot capture. This decomposition sets the stage for understanding why partnership types evolved differently over time and across policy environments.

I am also able to provide additional context for the sharp substitution from marriage to cohabitation that occurred in the mid-1990s. The estimates show that this turning point is driven not by a decline in the overall value of partnerships, but by a relative shift: the gains from marriage formation fell while the costs of cohabitation decreased. This change made cohabitation a more attractive alternative to marriage, even as the total number of partnerships stabilized. The timing of this substitution coincides with important institutional changes, particularly reforms in paternity establishment that altered the incentives facing unmarried parents (Rossin-Slater, 2017), as well as changes to government assistance for single mothers. While it is difficult to disentangle the effects of these overlapping policies, the evidence points to a net reduction in the relative value of marriage compared to cohabitation. In this framework, broad shifts in social norms or attitudes toward marriage—often referred to as "cultural drift" (Sassler and Lichter, 2020)—would be reflected in smooth, gradual changes in the estimated match surplus rather than discrete shifts in formation or dissolution costs. The presence of two clear inflection points in the data is therefore inconsistent with a pure cultural-drift explanation. Instead, the results suggest that evolving economic and institutional factors account for much of the observed transition, even if cultural influences may shape the broader environment in which these changes occur.

My third finding is that the 2008 financial crisis marks a second inflection point in household formation, when individuals became increasingly likely to remain single rather than enter either marriage or cohabitation. Following Lafortune and Low (2017) and Lafortune and Low (2023), I explore the role of assets in this shift by linking the structural model estimates

to housing prices. Counterfactual simulations that fix housing costs at their 2010 level show that lower prices increase marriage formation and divorce rates, leading to a modest net rise in the stock of married couples. These results highlight how housing and asset access shape both the entry into and stability of partnerships, consistent with the idea that the financial crisis amplified existing economic barriers to family formation. Together with the earlier evidence on rising formation costs and unequal returns to partnership, these findings underscore the importance of modelling partnership dynamics as a set of evolving flows rather than static stocks.

Relation to the literature

This paper builds on the transferable-utility (TU) marriage-matching framework of Becker (1973) and the empirical implementation of Choo and Siow (2006) (CS). The key insight of the CS approach is to combine Beckers two-sided matching model with a discrete-choice structure (McFadden, 1974), which delivers an empirically tractable system for recovering marital surplus. A large literature has extended this framework in static environments, for example by endogenizing meeting rates (Jaffe and Weber, 2019), incorporating cohabitation and peer effects (Mourifié and Siow, 2021), allowing for more flexible taste heterogeneity (Galichon and Salanié, 2022), or weakening identification requirements (Gualdani and Sinha, 2023). Imperfectly transferable utility (ITU) variants have also been developed to accommodate matching frictions and transfer costs (Galichon et al., 2019).

Closer to this paper are dynamic versions of the CS model. Choo (2015) allow agents to compare current and future payoffs from marriage when deciding whether to remain single, and Mourifié (2019) show that such a framework can be rationalized using a static model with peer effects. However, these models are effectively stationary: their parameters can be identified from a single cross-section, so they do not capture calendar-time changes in household formation. Chen and Choo (2023) extend the analysis to a non-stationary environment and propose a parametric estimator to address the curse of dimensionality. What these contributions have in common is that they treat match dissolution as exogenous.

This paper departs from that approach in three ways. First, I model separation as endogenous, in the spirit of work on divorce and marriage with match-quality shocks (Weiss and Willis, 1997; Brien et al., 2006; Bruze et al., 2015; Goussé et al., 2017), and in line with recent CS-style approaches with endogenous separation (Ciscato, 2024; Reynoso, 2024). Second, I allow for both marriage and cohabitation in the same empirical framework, which is essential for studying the second demographic transition. Third, and most importantly, I estimate the model in a non-stationary setting, so that match surplus, match-formation costs, and

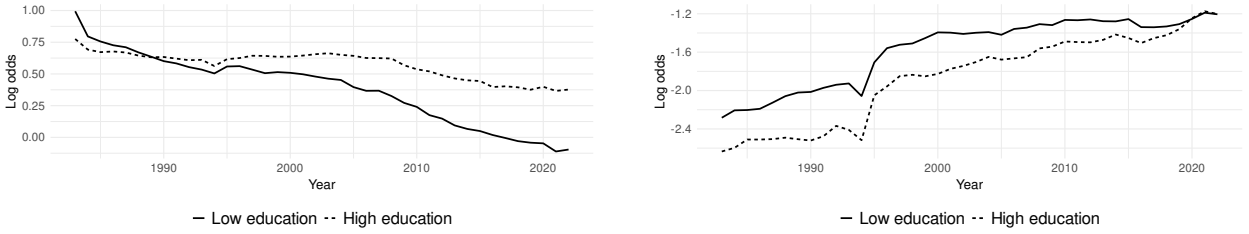
dissolution costs can evolve over calendar time. This feature is what allows the model to rationalize the facts that I document below.

The remainder of the paper proceeds as follows. Section 2 documents three key facts about the second demographic transition in the United States, which motivate the theoretical framework that follows. Section 3 presents the dynamic, non-stationary marriage-matching model and outlines identification and estimation. Section 4 describes the data and the reconstruction of historical cohabitation rates. Section 5 reports the main estimation results and counterfactual analyses. Section 6 concludes.

2 Three facts about the second demographic transition

This section documents three empirical regularities that characterize the second demographic transition in the United States. These stylized facts are drawn from four decades of monthly data from the Current Population Survey (CPS), a nationally representative labour-force survey conducted by the U.S. Census Bureau and the Bureau of Labor Statistics.[3] Education levels E are defined as low (L) for individuals with some college or less and high (H) for those with a college degree or more. I focus on individuals aged 24–40 to ensure that education reflects completed attainment rather than ongoing enrolment: many individuals aged 18–24 are classified as "low" education simply because they are still in school. This age restriction is maintained throughout the analysis of educational-attainment groups.

Fact 1 (Declining marriage and rising cohabitation)**.** *Marriage rates have declined while cohabitation has risen since the 1980s, for both low- and high-education individuals.*



(a) Married vs. single by education level

(b) Cohabiting vs. single by education level

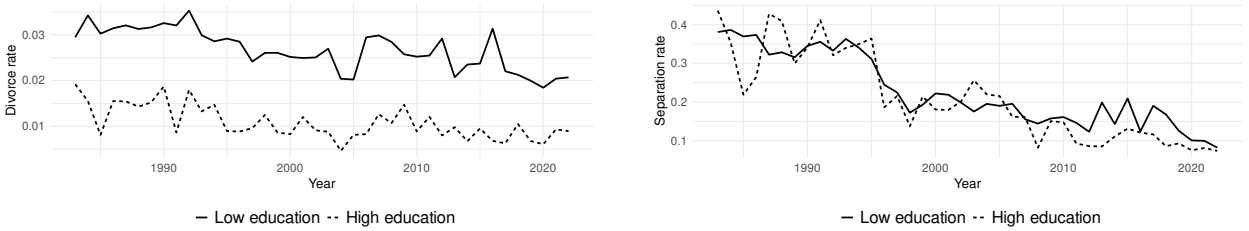
Figure 1: Log-odds of being married or cohabiting relative to being single, by education level.

To compare trends across groups of different sizes, I report the log-odds of being married or

[3]All data presented in this section come from the monthly CPS. The data construction and variable definitions are described in Section 4. Additional figures are provided in Appendix B.1.

cohabiting relative to being single for each education group,[4] allowing a consistent measure of relative prevalence over time. Figure 1a shows the uneven retreat from marriage—also documented by Lundberg et al. (2016)—and the corresponding rise in cohabitation is given in Figure 1b. During the first three decades of the transition, adults with at least a college degree were largely insulated from the decline in marriage, but this pattern reversed after 2008. Non-marital cohabitation became increasingly prevalent over the same period. While cohabitation rates rose sharply for both education groups, they levelled off for low-education individuals but continued to climb among those with higher education.

Fact 2 (Increasing match stability)**.** *Both marriage and non-marital cohabitation are more stable today than in the past.*



(a) One-year divorce hazard

(b) One-year separation hazard

Figure 2: One-year dissolution hazards for marriage and cohabitation.

When Lesthaeghe and Van de Kaa (1986) first outlined the features of the second demographic transition, divorce was expected to remain high. Instead, divorce rates peaked around 1980—shortly after the introduction of unilateral-divorce legislation (Wolfers, 2006)—and have since declined steadily. Separation rates among cohabiting couples have also fallen, though cohabitation remains far less stable than marriage. The joint pattern of declining formation and declining dissolution is central to understanding the modern marriage market: fewer partnerships form, yet those that do are more stable than at any previous point.

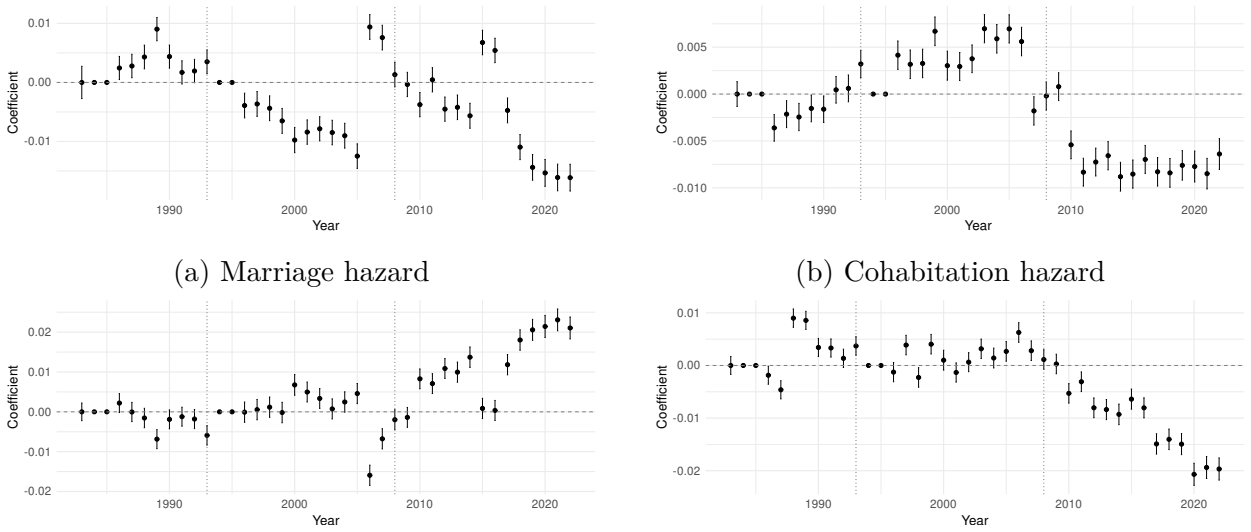
Fact 3 (Two inflection points in household formation)**.** *Two clear inflection points mark the long-run evolution of household formation patterns:*

(a) In the mid-1990s, individuals became more likely to cohabit and less likely to marry.

(b) Beginning in the early 2010s, individuals increasingly remained single and fertility declined sharply.

Figure 3 summarizes these changes in one-year hazard rates. The first phase of the transition corresponds to substitution from marriage toward cohabitation; the second marks a regime in

[4]For group E, the log-odds ratio at time t is defined as $\log[\#\text{Married}_t(E)/\#\text{Single}_t(E)]$ or $\log[\#\text{Cohabiting}_t(E)/\#\text{Single}_t(E)]$.



(a) Marriage hazard

(b) Cohabitation hazard

(c) Singlehood hazard

(d) Fertility hazard

Figure 3: One-year hazards for key demographic events.

Notes: Figures plot year fixed effects (α_t) from regressions of the form $d_{ist} = \alpha_t + \alpha_s + \beta X_{ist} + \varepsilon_{ist}$, anchored so that 1983 is the reference year. The dependent variable d_{ist} equals one if event d occurred for respondent i in state s during the past year. Controls X_{ist} include education, age, and race; standard errors are clustered by state.

which remaining single became increasingly common. I refer to these as the first and second inflection points of the second demographic transition. Figure 3d also shows that fertility declined substantially after the 2008 financial crisis, consistent with evidence in Kearney et al. (2022). While fertility is not modelled in this paper, the framework can be extended to incorporate it, as discussed in Appendix A.3. Together, these three facts capture the central patterns in household formation that the dynamic, non-stationary marriage-matching model developed in Section 3 is designed to explain.

3 Matching model

3.1 Motivation

The empirical evidence in Section 2 shows two features that standard, stock-based matching models have trouble rationalizing at the same time: (i) the flow of new partnerships has declined, but (ii) the partnerships that do form are more stable. This suggests that both *entry* margins (match-formation costs, search frictions, institutional or cultural barriers) and *exit* margins (dissolution costs, financial lock-in) are moving over time. A simple three-period example shows why observing flows, rather than only stocks, is crucial.

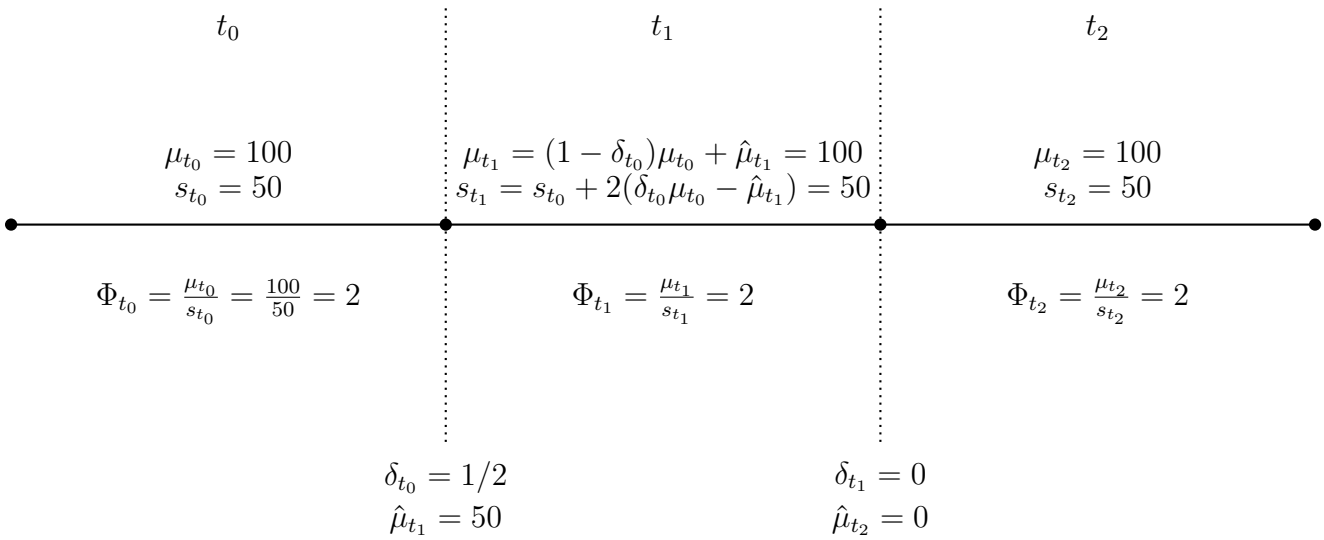


Figure 4: Simple three-period case—a numeric example

Consider a closed population observed in periods $t = t_0, t_1, t_2$. Let μ_t be the stock of existing matches and s_t the stock of singles. At the *end* of period t, a fraction $\hat{\delta}_t$ of existing matches dissolves (the separation rate); at the *start* of period $t+1$, $\hat{\mu}_{t+1}$ new matches form. The laws of motion are

$$\mu_t = (1 - \hat{\delta}_{t-1})\mu_{t-1} + \hat{\mu}_t \quad \text{and} \quad s_t = s_{t-1} + 2\Big(\hat{\delta}_{t-1}\mu_{t-1} - \hat{\mu}_t\Big).$$

Suppose an econometrician only observes the midpoint stocks (μ_t, s_t) and constructs a Choo–Siow-style surplus proxy

$$\Phi_t = \frac{\mu_t}{s_t}, \tag{1}$$

which measures the gains to being matched relative to remaining single.

Figure 4 illustrates the problem. In period t_0 there are $\mu_{t_0} = 100$ matches and $s_{t_0} = 50$ singles, so $\Phi_{t_0} = 2$. Between t_0 and t_1 half of all matches dissolve, $\hat{\delta}_{t_0} = 1/2$, but exactly 50 new matches form at the start of t_1, so that $(\mu_{t_1}, s_{t_1}) = (100, 50)$ and $\Phi_{t_1} = 2$ again. Between t_1 and t_2 nothing happens, so $\Phi_{t_2} = 2$ as well. A researcher who only ever sees the stocks would conclude that the "surplus" is constant over time. This conclusion is clearly wrong once flows are observed. The period t_0 stock contains many low-quality matches—half of them dissolve. By t_2 the stock is entirely composed of matches that have survived at least one period without separation. In other words, the *composition* of matches has improved even though the stock-based surplus proxy has not changed. This is exactly the situation observed in the data: fewer matches form, but those that do are more stable.

This example also motivates why I need to model formation and dissolution costs separately. In this simple exercise I have abstracted from both types of costs to focus on how flows reveal composition effects that are hidden in stocks. Once these costs are introduced, however, they become essential for distinguishing mechanisms that generate similar aggregate patterns. A fall in observed separations could reflect genuinely higher per-period surplus, but it could just as well reflect higher dissolution costs that trap couples together, as in the "separate spheres" model of Lundberg and Pollak (1993). Likewise, fewer new matches could reflect lower expected surplus, or instead higher formation costs—monetary (housing, moving, wedding) or non-monetary (search effort, weaker social networks, changing cultural norms around commitment). Without flows, these forces are not separately identified; with flows, the dynamic, non-stationary model in the next subsection can tell apart "fewer matches because it is harder to start them" from "fewer matches because staying together became costly to reverse."

3.2 Environment and benchmark

The model describes a bipartite matching market in which men and women form and dissolve co-residential partnerships over time. Men $i \in \mathcal{I}$ and women $j \in \mathcal{J}$ are each endowed with discrete types, denoted $x \in \mathcal{X} = \{x_1, \ldots, x_p\}$ and $y \in \mathcal{Y} = \{y_1, \ldots, y_q\}$. Time is discrete and indexed by $t = 1, \ldots, T$, where each period represents one calendar year. Let $m_t(x)$ and $f_t(y)$ denote the number of men and women of each type in period t. These population counts are treated as exogenousmortality, fertility, and migration are not modelled explicitlyand may vary across time. Agents can form one of two co-residential arrangements: non-marital cohabitation (C) or marriage (M), denoted $r \in \mathcal{R} = \{C, M\}$. A match is therefore defined by the tuple $(x, y; r)$, representing a man of type x and a woman of type y in arrangement r. At any moment, the population consists of singles $\mu_t(x, 0)$ and $\mu_t(0, y)$ and of existing matches $\mu_t^r(x, y)$.

Before introducing the full model, it is useful to clarify how I use the terms *static*, *dynamic*, and *non-stationary*, since each involves a notion of time. In a static model, agents are myopic and make no forward-looking decisions, whereas in a dynamic model, they evaluate expected future payoffs when choosing optimally today. Stationarity, by contrast, concerns how population counts and behavioural parameters evolve over calendar time. A stationary model assumes a closed population in steady state, while a non-stationary model allows these quantities to change exogenously or endogenously through agents decisions. Both static and dynamic models can be either stationary or not; the distinction lies in the treatment of forward-looking behaviour. A dynamic, non-stationary framework therefore provides the

flexibility to estimate time-varying behavioural parameters, capturing how preferences and constraints evolve across calendar time. This stands in contrast to dynamic but stationary frameworks—such as Choo (2015) or Ciscato (2024)—which describe life-cycle dynamics in a fixed environment but not long-run aggregate transitions.

To build intuition, I begin with a static, stationary benchmark that extends the transferable-utility framework of Choo and Siow (2006) to allow for both marriage and cohabitation. This benchmark serves as a reference point for the dynamic, non-stationary model that follows. In each period, men of type x and women of type y may form one of two arrangements, $r \in \mathcal{R} = \{C, M\}$, or remain single. A match $(x, y; r)$ generates a total surplus $S^r(x, y)$ representing the gains to partnership relative to singlehood. Under transferable utility, the man and woman receive shares $\theta^r(x, y)$ and $1 - \theta^r(x, y)$ of this surplus, and each faces an idiosyncratic taste shock $\varepsilon_i^r(x, y)$ or $\varepsilon_j^r(y, x)$. The resulting utilities are

$$V_i^r(x, y) = \theta^r(x, y)S^r(x, y) + \varepsilon_i^r(x, y) \tag{2}$$

and

$$V_j^r(y, x) = [1 - \theta^r(x, y)]S^r(x, y) + \varepsilon_j^r(y, x), \tag{3}$$

while remaining single yields $V_i(x, 0) = \varepsilon_i^{\{0\}}(x, 0)$ and $V_j(0, y) = \varepsilon_j^{\{0\}}(0, y)$.

If the preference shocks are i.i.d. Type-I extreme value, then the equilibrium matching probabilities follow directly from the multinomial-logit formulation of McFadden (1974). In equilibrium, the number of $(x, y; r)$ matches satisfies the marriage-matching function

$$\mu^r(x, y) = \exp\left\{\frac{S^r(x, y)}{2}\right\}\sqrt{\mu(x, 0)\mu(0, y)}, \tag{4}$$

which implies the non-parametric surplus estimator

$$\phi^r(x, y) = \log\left(\frac{\mu^r(x, y)^2}{\mu(x, 0)\mu(0, y)}\right). \tag{5}$$

This static benchmark provides a tractable measure of the gains to matching using cross-sectional data on singles and couples across both arrangements. Although it captures the basic structure of household formation, it abstracts from forward-looking behaviour, endogenous separation, and evolving population stocks. The dynamic, non-stationary model developed in the next subsection extends this environment precisely along these dimensions.

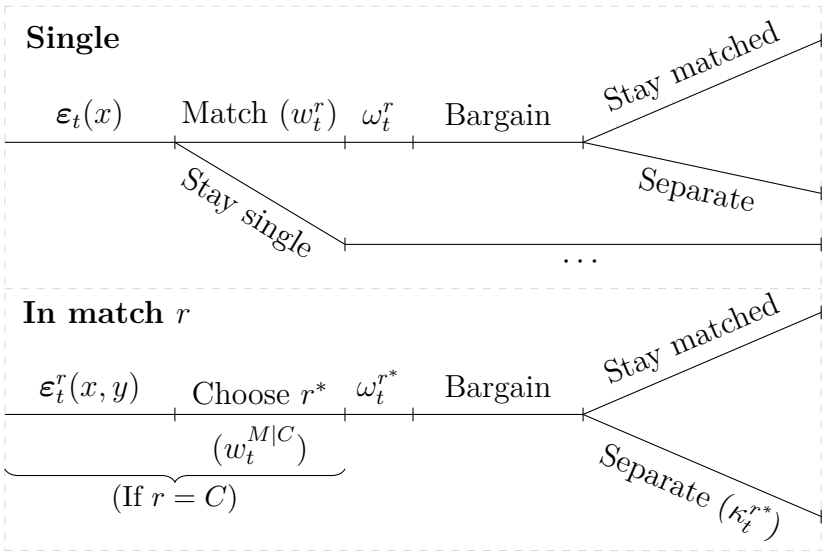


Figure 5: Decision-making process within a period

3.3 Generalized non-stationary dynamic model

I will now extend the model to a dynamic and non-stationary environment. Before that, however, I will outline how agents make decisions in the dynamic model by considering all possible choices an agent can make in time period t conditional on their present match status. To do this, some notation must be introduced. If a $(x, y; r)$ match is formed in period t, this incurs a match-formation cost $w_t^r(x, y)$ split between the two members of the match according to an exogenously-given sharing rule $\eta_t^r(x, y) \in [0, 1]$. If an existing match is dissolved, this incurs a match-dissolution cost $\kappa_t^r(x, y)$ which is also split according to some exogenously-given sharing rule $\lambda^r(x, y) \in [0, 1]$.[5] One can think of $\eta_t^r(x, y)$ and $\lambda^r(x, y)$ being fixed by either legal or cultural means. For example, if a couple is getting married, part of $w_t^r(x, y)$ is the cost of the wedding.[6] As in the static case, agents and couples will have preference shocks over different types of the opposite sex and arrangements, respectively. The convention will be that ε is used to denote preference shocks. Couples are also subject to a match-quality shock each period. In general, these quality shocks will be denoted by ω. Now that the notation has been established, the decision-making process can be discussed.

Figure 5 describes the dynamic decision-making process for both singles and couples. At the start of the period, singles will observe their preference shock $\boldsymbol{\varepsilon}_t(x)$ and choose to match or remain single. If they form an $(x, y; r)$ match, this incurs a cost $w_t^r(x, y)$. Once the

[5] I am assuming these cost-sharing parameters are given because from what I observe, these parameters cannot be separately identified.

[6] In North America this cost is traditionally borne by the family of the bride. `https://www.vogue.com/article/who-pays-for-the-wedding-etiquette-rules`

match forms, the couple's match quality shock ω_t^r is revealed. After this, they bargain over the match surplus and as a result of this process decide to remain together or separate. Separation incurs a cost $\kappa_t^r(x,y)$. If they separate, both agents reenter the matching market in the next period as singles. If a single agent chooses to remain single, they wait out the remainder of the period and reenter in $t+1$. If a couple begin a period in an $(x,y;C)$ match, they first observe their preference shock which is over remaining cohabiting or transitioning to marriage. After the preference shock is revealed, if they transition to marriage, this incurs a switching cost $w_t^{M|C}(x,y)$. If they remain cohabiting, there is no cost. After choosing their optimal arrangement r^* they observe a match quality shock $\omega_t^{r^*}$ and choose to remain together or dissolve the match and pay the separation cost $\kappa_t^{r^*}(x,y)$. If they are in an $(x,y;M)$ match, there is no preference shock over possible arrangements since I assume that couples cannot transition from marriage to cohabitation.

3.4 Decision-making for singles

Consider two individuals i and j in an $(x,y;r)$ match in time t. The dynamic match surplus is the sum of per-period payoffs and the continuation values less the individual's reservation values. I'll assume that agents discount the future at a known and constant rate $\beta \in [0,1]$. The match value can be written as

$$V_{ijt}^r(x,y) = \underbrace{S_t^r(x,y) + \omega_{ijt}^r}_{\text{per-period utility}} + \underbrace{\beta \mathbb{E} V_{i,t+1}^r(x',y';\theta_{t+1}^r,\Omega_{t+1}^r) + \beta \mathbb{E} V_{j,t+1}^r(y',x';\theta_{t+1}^r,\Omega_{t+1}^r)}_{\text{continuation values}} - \tag{6}$$
$$\underbrace{\left[\beta \mathbb{E} V_{i,t+1}^S(x',\varepsilon_{t+1}(x')) - \lambda^r(x,y)\kappa_t^r(x,y)\right] - \left[\beta \mathbb{E} V_{j,t+1}^S(y',\varepsilon_{t+1}(y')) - (1-\lambda^r(x,y))\,\kappa_t^r(x,y)\right]}_{\text{reservation values}}.$$

The per-period utility is a sum of per-period surplus $S_t^r(x,y)$ and the couple-specific quality shock ω_{ijt}^r. The continuation values represent each agent's expected gain if they remain matched in the next period in arrangement r'. These values also depend on their future types x' and y' which are assumed to evolve either deterministically—e.g., age—or if types are education, not at all. Finally, the payoff associated with being matched next period also depends on the equilibrium transfers represented by the bargaining share θ_{t+1}^r and the possible set of shocks the agents will face in the next period Ω_{t+1}^r. The reservation values captures the utility the agents would receive if they are on the market again next period less their share of the separation costs. This is the amount they forgo by remaining matched.

As in Goussé et al. (2017) and Ciscato (2024), I assume that couples bargain over the surplus generated by a match and will split $V_{ijt}^r(x,y)$ according to the sharing rule $\theta^r(x,y)$. This can be summarized in the following proposition.

Proposition 1. *Suppose that the total surplus of an $(x, y; r)$ match for individuals i and j in time t is given by Equation 6. Also assume that this quantity is shared through Nash bargaining, then there exists a transfer $\tau_{ijt}^{r*}(x, y; \theta_t^r, \lambda_t^r, \omega_t^r)$ from the woman to the man such that:*

1. *The man receives $\theta_t^r(x, y)V_{ijt}^r(x, y)$;*
2. *The woman receives $[1 - \theta_t^r(x, y)]\, V_{ijt}^r(x, y)$.*

Furthermore, a match will persist from one period to the next if and only if $V_{ijt}^r(x, y) > 0$.

Proof. See Appendix A.1. □

Abusing the notation and terminology slightly, I will define

$$\begin{aligned}\pi_t^r(x, y) &= S_t^r(x, y) + \beta\mathbb{E}V_{i,t+1}^r(x', y'; \theta_{t+1}^r, \Omega_{t+1}^r) + \beta\mathbb{E}V_{j,t+1}^r(y', x'; \theta_{t+1}^r, \Omega_{t+1}^r) \\ &\quad - \beta\mathbb{E}V_{i,t+1}^S(x', \varepsilon_{t+1}(x')) - \beta\mathbb{E}V_{j,t+1}^S(y', \varepsilon_{t+1}(y')) \\ &= S_t^r(x, y) + \beta\overline{S}_{t+1}^r(x', y')\end{aligned}$$

to be the sum of current period surplus and expected future payoffs. Going forward, I will simply refer to the systematic term $\pi_t^r(x, y)$ as surplus which is not to be confused with $V_{ijt}^r(x, y)$ which represents *total* surplus which also includes the match-quality shock and separation cost. Given this simplification I can write the total match surplus as

$$V_{ijt}^r(x, y) = \underbrace{\pi_t^r(x, y)}_{\text{Surplus}} + \underbrace{\kappa_t^r(x, y)}_{\text{Sep. cost}} + \underbrace{\omega_{ijt}^r}_{\text{Shock}}. \tag{7}$$

As established in Proposition 1, a match will persist if and only if

$$\begin{aligned}&V_{ijt}^r(x, y) > 0 \\ \iff &\underbrace{\pi_t^r(x, y)}_{\text{Surplus}} + \underbrace{\omega_{ijt}^r}_{\text{Shock}} > -\underbrace{\kappa_t^r(x, y)}_{\text{Sep. cost}}.\end{aligned}$$

As described in Figure 5, the match-quality shock is only revealed after a match is formed. Therefore, when assessing the return to a possible match, agents consider the expected match value given by

$$\overline{V}_t^r(x, y) = \mathbb{E}\max\{\pi_t^r(x, y) + \omega_{ijt}^r, -\kappa_t^r(x, y)\}. \tag{8}$$

Putting this all together, one may write the level of utility a single man i of type x receives if he matches with a woman of type y in arrangement r and do the same for a single woman

j in an $(x, y; r)$ match. The vector of preference shocks faced by man i of type x in time t is given by

$$\boldsymbol{\varepsilon}_{it}(x) = \left(\varepsilon_{it}^{\{0\}}(x,0), \varepsilon_{it}^{C}(x,y_1), \varepsilon_{it}^{C}(x,y_2), \cdots, \varepsilon_{it}^{C}(x,y_q), \varepsilon_{it}^{M}(x,y_1), \varepsilon_{it}^{M}(x,y_2), \cdots, \varepsilon_{it}^{M}(x,y_q)\right).$$

and similarly for woman j of type y,

$$\boldsymbol{\varepsilon}_{jt}(y) = \left(\varepsilon_{jt}^{\{0\}}(0,y), \varepsilon_{jt}^{C}(y,x_1), \varepsilon_{jt}^{C}(y,x_2), \cdots, \varepsilon_{jt}^{C}(y,x_p), \varepsilon_{jt}^{M}(y,x_1), \varepsilon_{jt}^{M}(y,x_2), \cdots, \varepsilon_{jt}^{M}(y,x_p)\right).$$

This set of preference shocks is analogous to the static case, and the dynamic-stationary case, but with the addition of time subscripts. Taking into consideration that agents will split the match-formation cost $w_t^r(x,y)$ according to a sharing rule $\eta_t^r \in [0,1]$, the value a single agent would get from entering a match may be written as

$$V_{it}^{S,r}(x,y) = \theta_t^r(x,y)\overline{V}_t^r(x,y) - \eta_t^r(x,y)w_t^r(x,y) + \varepsilon_{it}^r(x,y)$$

and

$$V_{jt}^{S,r}(y,x) = \left[1-\theta_t^r(x,y)\right]\overline{V}_t^r(x,y) - \left[1-\eta_t^r(x,y)\right]w_t^r(x,y) + \varepsilon_{jt}^r(x,y).$$

As in the static case, assume the flow payoff of singlehood is normalized to zero so that for men and women these are given by

$$V_{it}^{S}(x,0) = \varepsilon_{it}^{\{0\}}(x,0)$$

and

$$V_{jt}^{S}(0,y) = \varepsilon_{jt}^{\{0\}}(0,y),$$

respectively. The expressions $V_{it}^{S,r}(x,y)$ and $V_{jt}^{S,r}(y,x)$ are the generalized dynamic and non-stationary equivalents of Equations 2 and 3, respectively. Therefore, singles in the dynamic model face a nearly identical problem to that of the static case whereby they solve

$$V_{it}^{S}(x) = \max_{y\in\mathcal{Y}\cup\{0\}, r\in\mathcal{R}} \{V_{it}^{S,r}(x,y)\}_{r\in\mathcal{R}}^{y\in\mathcal{Y}\cup\{0\}} \text{ and } V_{jt}^{S}(y) = \max_{x\in\mathcal{X}\cup\{0\}, r\in\mathcal{R}} \{V_{jt}^{S,r}(y,x)\}_{r\in\mathcal{R}}^{x\in\mathcal{X}\cup\{0\}}. \quad (9)$$

3.4.1 Marriage matching function

Before deriving the marriage matching function, I will introduce the concept of an equilibrium dynamic and non-stationary matching market.

Definition 1. *An equilibrium in the matching market in time t is a vector of singles*

$[\{\mu_t(x,0)\}_{x\in\mathcal{X}}, \{\mu_t(0,y)\}_{y\in\mathcal{Y}}]$ *and a vector of bargaining weights* $\{\theta_t^r(x,y)\}_{x\in\mathcal{X},y\in\mathcal{Y}}$ *such that the number of singles of type* x *men who want to match with type* y *women in arrangement* r *is equal to the number of singles of type* y *women who want to match with type* x *men in arrangement* r*.*

Let $\hat{\mu}_t^r(x,y)$ be the number of *new* x,y matches of arrangement r in time t. Furthermore, I'll denote the number of type x and y individuals who choose to remain single in time t to be $\hat{\mu}_t(x,0)$ and $\hat{\mu}_t(0,y)$, respectively. This allows me to derive a non-stationary version of the MMF of Ciscato (2024).

Proposition 2. *Suppose that the marriage market is in equilibrium at time* t*. If the preference shocks* $\boldsymbol{\varepsilon}$ *are assumed to be i.i.d. Type I extreme-value distributed then for an* $(x,y;r)$ *match the matching function has the form*

$$\hat{\mu}_t^r(x,y) = \exp\left(\frac{\overline{V}_t^r(x,y) - w_t^r(x,y)}{2}\right)\sqrt{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)} \tag{10}$$

for all $(x,y;r) \in \mathcal{X}\times\mathcal{Y}\times\mathcal{R}$*. Furthermore, the matching is feasible in the sense that it satisfies the population accounting constraints and the law of motion.*

Proof. See Appendix (A.2). □ □

3.5 Decision-making for couples

The decision-making process for couples depends on their current arrangement r. Consider individuals i and j of types x and y who are matched in time t in arrangement C. At the start of the period, they face a joint preference shock r over remaining in arrangement C or transitioning to marriage (M). Once the preference shock over is revealed, the couple will then consider the expected value of each possible arrangement and the transition cost. That is, they face the discrete choice problem

$$\max\{\overline{V}_t^M(x,y) - w_t^{M|C}(x,y) + \varepsilon_{ijt}^M(x,y), \overline{V}_t^C(x,y) + \varepsilon_{ijt}^C(x,y)\}. \tag{11}$$

After they choose $r^* \in \{C,M\}$, the match-quality shock $\omega_{ijt}^{r^*}$ is revealed and they bargain over the utility generated by the match. This value of the match is the same as that which is given in Equation 7. To simplify calculations, I will make an assumption about the distribution of the preference and match-quality shocks.

Assumption 1. *Assume that that elements of the set of preference shocks* $\boldsymbol{\varepsilon}_{ijt}(x,y) = [\varepsilon_{ijt}^M(x,y), \varepsilon_{ijt}^C(x,y)]$ *are independent from the elements of set of match-quality shocks* $\boldsymbol{\omega}_{ijt} =$

$[\omega_{ijt}^M, \omega_{ijt}^C]$. *Furthermore, assume the elements of* $\boldsymbol{\varepsilon}_{ijt}$ *and* $\boldsymbol{\omega}_{ijt}$ *are i.i.d. GEV I distributed.*

Under Assumption 1 there exists simple closed-form expressions for three different probabilities that will be needed to solve the model.

The probability that a couple transitions from arrangement C to arrangement M is given by

$$\mathbb{P}_t(M|x,y,C) = \frac{\exp\left\{\overline{V}_t^M(x,y) - w_t^{M|C}(x,y)\right\}}{\exp\left\{\overline{V}_t^M(x,y) - w_t^{M|C}(x,y)\right\} + \exp\left\{\overline{V}_t^C(x,y)\right\}}.$$

Let $d_{ijt}^r(x,y) \in \{0,1\}$ be an indicator which is equal to one if individuals i and j in an $(x,y;r)$ match in time t dissolve their relationship, and zero otherwise. The probability that this event occurs is given by

$$\mathbb{P}_t\left(d_{ijt}^r(x,y)=1\right) = \left(1+\exp\{\pi_t^r(x,y)+\kappa_t^r(x,y)\}\right)^{-1}. \tag{12}$$

Finally, given that the preference shocks $\boldsymbol{\varepsilon}_{ijt}^r$ and match-quality shocks $\boldsymbol{\omega}_{ijt}^r$ are assumed to be independent of one another, the probability that an $(x,y;C)$ match successfully transitions to an $(x,y;M)$ can be written as

$$\mathbb{P}_t(M|x,y,C)\mathbb{P}_t\left(d_{ijt}^r(x,y)=1\right) = \frac{\exp\left\{\overline{V}_t^M(x,y) - w_t^{M|C}(x,y)\right\}\left(1+\exp\{\pi_t^r(x,y)+\kappa_t^r(x,y)\}\right)^{-1}}{\left[\exp\left\{\overline{V}_t^M(x,y) - w_t^{M|C}(x,y)\right\} + \exp\left\{\overline{V}_t^C(x,y)\right\}\right]}.$$

3.5.1 Model closure and link to identification

Having defined the dynamic and non-stationary structure above, I now describe how the model is closed and how the systematic surplus terms $S_t^r(x,y)$ are linked to observables. In the preceding sections, the dynamic environment was defined recursively: given the current match surplus $S_t^r(x,y)$, agents form expectations about future utilities through the continuation values $\mathbb{E}V_{i,t+1}^r$ and $\mathbb{E}V_{j,t+1}^r$. These expectations govern both the persistence of existing matches and the formation of new ones. The remaining task is to connect these value functions to observed data in a way that remains consistent with forward-looking behaviour but does not require a full equilibrium solution.

Under transferable utility, the total match value satisfies

$$V_{ijt}^r(x,y) = S_t^r(x,y) + \omega_t^r + \kappa_t^r(x,y) + \beta\Big[\mathbb{E}V_{t+1}^r(x',y';\Omega_{t+1}^r) - \mathbb{E}V_{t+1}^S(x';\boldsymbol{\varepsilon}_{t+1}) - \mathbb{E}V_{t+1}^S(y';\boldsymbol{\varepsilon}_{t+1})\Big], \tag{13}$$

where the continuation values represent the discounted gains from remaining matched rather

than re-entering the singles market. Equation (13) summarizes how current-period surplus, match-quality shocks, and separation costs jointly determine the persistence of a match over time.

Rather than solving this Bellman system through backward induction or a contraction mapping—as in standard dynamic discrete-choice (DDC) models (e.g. Rust, 1987)—I adopt a reduced-form approach that relies on observed choice probabilities. Agents are assumed to know their own formation and dissolution costs, as well as the expected value of each possible state, but the econometrician does not need to model how these expectations are formed or to re-solve the global dynamic program. Instead, I recover expected values directly from the data using the observed conditional choice probabilities (CCPs) implied by the models structure. This approach follows the logic of the DDC literature—linking per-period payoffs to CCPs—but avoids imposing strong assumptions about belief formation or equilibrium updating, which are often difficult to justify in a setting with aggregate non-stationarity.

For each match type $(x, y; r)$, the observed probability of a transition—formation, persistence, or dissolution—identifies the corresponding expected value function up to a normalization. Because the dynamic matching function in Proposition 2 expresses flows in terms of $\overline{V}_t^r(x, y)$, these CCPs can be inverted to recover $\overline{V}_t^r(x, y)$ and, in turn, the systematic surplus $S_t^r(x, y)$. Intuitively, the mapping from observed transitions to expected values provides a reduced-form representation of agents' forward-looking behaviour: higher continuation values are reflected in greater persistence probabilities and lower dissolution hazards, while higher formation costs reduce the probability of entering a match. This structure allows the model to be closed period by period without solving for a global fixed point, maintaining tractability while preserving a dynamic interpretation.

Finally, the estimated mapping from relevant state variables—including, for example, local housing prices—to expected values provides a direct empirical link between economic conditions and household-formation outcomes. In counterfactual simulations, this mapping can be used to extrapolate how expected match values and partnership flows would respond to shifts in these state variables, without re-solving the full dynamic equilibrium. In this sense, the framework nests the standard equilibrium solution as a special case but remains computationally feasible and empirically transparent. The next subsection formalizes these ideas by showing precisely how the observed transition probabilities identify the key structural components.

3.6 Identification

I'll now describe how to identify the model quantities from both the stocks and flows of population counts. In particular, I am interested in identifying the expected match value $\overline{V}_t^r(x,y)$, match-formation cost $w_t^r(x,y)$, match-transition costs $w_t^{r|r}(x,y)$, match-dissolution cost $\kappa_t^r(x,y)$, male bargaining weight $\theta_t^r(x,y)$, and the surplus term $\pi_t^r(x,y)$. However, before I can do that, I'll need to establish some notation and a few assumptions regarding what is observable.

Let $\tilde{\mu}_t^r(x,y)$ be the number of $(x,y;r)$ matches at the start of period t. As before, $\hat{\mu}_t^r(x,y)$ will denote the number of new $(x,y;r)$ matches that form in period t, and $\hat{\mu}_t(x,0)$ and $\hat{\mu}_t(0,y)$ represents the number of men and women who begin and end period t single. I'll denote $\hat{\mu}_t^{M|C}(x,y)$ to be the number of couples who began period t in an $(x,y;C)$ match and transitioned to $(x,y;M)$. The proportion of couples who began period t in an $(x,y;r)$ match and separated is given by $\hat{\delta}_t^r(x,y)$. Finally, the proportion of couples who entered an $(x,y;r)$ match in time t and also dissolved that match within the same period will be denoted as $\hat{\hat{\delta}}_t^r(x,y)$. I will now establish some identification results.

Proposition 3. *Expected match value $\overline{V}_t^r(x,y)$ is identified from the match-dissolution rate $\hat{\delta}_t^r(x,y)$.*

Proof. Recall the expected value of an $(x,y;r)$ match in time t is given by

$$\begin{aligned}\overline{V}_t^r(x,y) &= \mathbb{E}\max\{\pi_t^r(x,y)+\omega_{ijt}^r, -\kappa_t^r(x,y)\} \\ &= \log\left(1+\exp\{\pi_t^r(x,y)+\kappa_t^r(x,y)\}\right)+\gamma\end{aligned}$$

where the second line follows from the parametric assumption on ω_{ijt}^r and $\gamma \approx 0.57722$ is the Euler-Mascheroni constant. Furthermore, recall that a match will persist if and only if $V_{ijt}^r(x,y) > 0$. Therefore, if one were to replace the left-hand side of Equation 12 with the observed dissolution rate $\hat{\delta}_t^r(x,y)$ this identifies $\pi_t^r(x,y)+\kappa_t^r(x,y)$ which provides $\overline{V}_t^r(x,y)$. □

Next I will discuss how to identify the match-formation cost and the male bargaining share from the matching function.

Proposition 4. *The match-formation costs $w_t^r(x,y)$ are identified from the matching function given in Equation 10 and the expected match value $\overline{V}_{ijt}^r(x,y)$. The bargaining share $\theta_t^r(x,y)$ comes from a step in the proof of Proposition 2.*

Proof. One can get $w_t^r(x,y)$ immediately by taking the natural log and inverting the match-

ing function:

$$\hat{\mu}_t^r(x,y) = \exp\left(\frac{\overline{V}_t^r(x,y) - w_t^r(x,y)}{2}\right)\sqrt{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)}$$
$$w_t^r(x,y) = \overline{V}_t^r(x,y) + \hat{\mu}_t(x,0) + \hat{\mu}_t(0,y) - 2\hat{\mu}_t^r(x,y). \tag{14}$$

Since the counts $\hat{\mu}_t(x,0)$, $\hat{\mu}_t(0,y)$, and $\hat{\mu}_t^r(x,y)$ are observed and $\overline{V}_t^r(x,y)$ is identified from Proposition 3, this implies $w_t^r(x,y)$ is identified.

To get the bargaining share $\theta_t^r(x,y)$, take the ratio of the demand and supply equations used to derive the matching function—see Appendix A.2.[7] This gives

$$\theta_t^r(x,y) = \frac{1}{2}\left[1 + \left[\log\hat{\mu}_t(0,y) - \log\hat{\mu}_t(x,0)\right]\left[\overline{V}_t^r(x,y) - w_t^r(x,y)\right]^{-1}\right]. \tag{15}$$

Since both $\overline{V}_t^r(x,y)$ and $w_t^r(x,y)$ are identified, so is $\theta_t^r(x,y)$. □

Now I'll establish identification results for the remaining parameters: match-transition costs $w_t^{r|r}(x,y)$, match-dissolution cost $\kappa_t^r(x,y)$, and per-period surplus $S_t^r(x,y)$.

Proposition 5. *The match-transition costs $w_t^{M|C}(x,y)$ are identified from counts of who transitions from C to M and counts of who begins the period in arrangement C and remains in that arrangement for the duration of the period.*

Proof. From Proposition 3, expected match value $\overline{V}_t^r(x,y)$ is identified. The probability that a couple in an $(x,y;C)$ match will choose to transition to marriage is given by

$$\mathbb{P}_t(M|x,y,C) = \frac{\exp\left\{\overline{V}_t^M(x,y) - w_t^{M|C}(x,y)\right\}}{\exp\left\{\overline{V}_t^M(x,y) - w_t^{M|C}(x,y)\right\} + \exp\left\{\overline{V}_t^C(x,y)\right\}}.$$

The probability that they remain in their current arrangement C is

$$\mathbb{P}_t(C|x,y,C) = 1 - \mathbb{P}_t(M|x,y,C) = \frac{\exp\left\{\overline{V}_t^C(x,y)\right\}}{\exp\left\{\overline{V}_t^M(x,y) - w_t^{M|C}(x,y)\right\} + \exp\left\{\overline{V}_t^C(x,y)\right\}}.$$

The maximum likelihood estimates for these probabilities are

$$\mathbb{P}_t(M|x,y,C) = \frac{\hat{\mu}_t^{M|C}(x,y)}{\tilde{\mu}_t^C(x,y)} \text{ and } \mathbb{P}_t(C|x,y,C) = \frac{\hat{\mu}_t^{C|C(x,y)}}{\tilde{\mu}_t^C(x,y)}.$$

[7] It should be noted that this requires additional assumptions. I have included this discussion in Appendix (A.2.1).

Therefore, by taking logs and rearranging, the switching cost $w_t^{M|C}(x,y)$ can be written as

$$w_t^{M|C}(x,y) = \overline{V}_t^M(x,y) - \overline{V}_t^C(x,y) + \log \hat{\mu}_t^{C|C}(x,y) - \log \hat{\mu}_t^{M|C}(x,y). \tag{16}$$

□

To identify the per-period surplus $\pi_t^r(x,y)$ and separation cost $\kappa_t^r(x,y)$ separately, I will make an assumption about matches which persist for a short duration.

Assumption 2. *(Instantaneous dissolution): Couples who form an $(x,y;r)$ match in time t and also dissolve that match within the same period incur no dissolution cost.*

The idea of Assumption 2 is that whether one thinks of costs as being psychic or monetary, both should be small—I assume here they are zero—if the duration of a match is less than one year. For example, a couple who have only been together for a short time are less likely to have accumulated join assets, including children, which would need to be shared upon match dissolution. Also, in a short marriage, often the couple can annul the marriage or file uncontested divorce which is much cheaper than formal divorce proceedings.

Proposition 6. *Given Assumption 2, the dissolution cost $\kappa_t^r(x,y)$ and the surplus $\pi_t^r(x,y)$ are identified separately.*

Proof. Proposition 3 shows that $\pi_t^r(x,y) + \kappa_t^r(x,y)$ is identified and $\pi_t^r(x,y)$ is pinned down by separately Equation 12 for the matches that dissolve in the period they form as

$$\hat{\hat{\delta}}_t^r(x,y) = \left(1 + \exp\{\pi_t^r(x,y)\}\right)^{-1}.$$

Therefore, $\kappa_t^r(x,y)$ is identified from the difference in between the instantaneous dissolution rate $\hat{\hat{\delta}}_t^r(x,y)$ and the non-instantaneous dissolution rate $\hat{\delta}_t^r(x,y)$. □

3.7 Estimation

In this section I'll describe how I estimate the quantities of interest in the model. These are for each $x \in \mathcal{X}$, $y \in \mathcal{Y}$, $r \in \{C, M\}$, and $t = 1, \cdots, T$; expected match value $\overline{V}_t^r(x,y)$, match-formation cost $w_t^r(x,y)$, transition cost $w_t^{M|C}(x,y)$, separation costs $\kappa_t^r(x,y)$, bargaining weight $\theta_t^r(x,y)$, and surplus $\pi_t^r(x,y)$. I am going to derive non-parametric estimators for these objects of interest defined purely in terms of observable sample quantities.

3.7.1 Types of individuals

The model is quite flexible in terms of how one can define types. For example, in the case of education, types are defined as high (H) and low (L) education categories as explained in Section 4. That is, the type space is $\mathcal{Z}_E = \mathcal{X}_E \times \mathcal{Y}_E = \{L, H\} \times \{L, H\} = \{LL, LH, HL, HH\}$. I also estimate the model defining type to be age group. In this case the set of types for men and women are $\mathcal{X}_A = \mathcal{Y}_A = \{a_{\leq 24}, a_{25-29}, a_{30-34}, a_{35-40}\}$. Thus the type space is $\mathcal{Z}_A = \mathcal{X}_A \times \mathcal{Y}_A$ and contains $|\mathcal{Z}_A| = 4^2 = 16$ many possible match types. It should be noted that the curse of dimensionality bites pretty quickly despite the large number of observations in the CPS. This is due to how divorce, separation, and new matches are measured—see Section 4.3—and the fact that in any given period, these events are actually quite rare. Another way to see this is that, even when considering the simplest possible type space $\mathcal{Z}_E$, if one factors in that there are 40 time periods, and 5 quantities to be estimated, and 2 possible match arrangements $\{C, M\}$, then this is 1600 parameters which need to be estimated.

It is worth mentioning that it need not be the case that $\mathcal{X} = \mathcal{Y}$. For example, as I show in Appendix B.3, sometimes it is natural to define the type space for either men or women to be more granular than the other. For example, one case I will explore below is where men are grouped into education-employment types but women are grouped only by education type. Additionally, as I will explore in Section 5, it is also possible consider match types where men and women are necessarily of the same type. One example of this is whether an individual lives in an urban or rural environment. In this case, $\mathcal{X} = \mathcal{Y} = \{U, R\}$ but we could assume that individuals in urban areas only match with those local to them, and thus also in urban areas. The same would then apply to those in rural areas. As such, the set of possible match types is no longer the Cartesian product of $\mathcal{X}$ and $\mathcal{Y}$ but rather, $\mathcal{Z} = \{UU, RR\}$. A similar logic can be applied to whether couples have children. I will explore this more in Section 5. I also discuss how the model can be easily extended to include fertility in Appendix A.3

3.7.2 Match-formation parameters

Here I will present closed-form expressions for all of the structural parameters in the model. Broadly speaking, these non-parametric estimators are derived from the identification results by replacing population values with their corresponding maximum likelihood estimates. That is, I take the results from Section 3.6 and simply replace theoretical population counts and separation rates with their empirical counterparts. In the spirit of Choo and Siow (2006), I have relatively simple closed-form expressions for all of the parameters. Similarly, these estimates are non-parametric in the sense that they will fit any observed household formation patterns. The downside of this approach is that I am unable to obtain standard errors for

my estimates. I'll summarize these expressions here and provide some interpretation of the estimated quantities in the cases where there is a meaningful behavioural context. To simplify the notation a bit, I will define

$$\Lambda_t^r(x,y) = \log\left(\frac{1-\hat{\delta}_t^r(x,y)}{\hat{\delta}_t^r(x,y)}\right) \tag{17}$$

which is the negative of the logit function or the inverse log odds. I'll break up this discussion into three separate categories: match-formation parameters, match-stability parameters, and the male bargaining share.

Let

$$\Phi_t^r(x,y) = \overline{V}_t^r(x,y) - w_t^r(x,y) \tag{18}$$

denote the expected gain to matching net of formation costs. This is estimated by taking the log of the matching function and rearranging to get

$$\Phi_t^r(x,y) = 2\log\hat{\mu}_t^r(x,y) - \log\hat{\mu}_t(x,0) - \log\hat{\mu}(0,y).$$

This is the non-stationary analog of the surplus estimate of Choo and Siow (2006) using flows instead of stocks. What is useful about observing both new matches and match dissolutions is that I can then decompose this to get both the expected match value and the formation cost. The expected match value $\overline{V}_t^r(x,y)$ is derived from the match-dissolution rate which is calculated using the method described in Section 4.3. From the proof of Proposition 3, for each $(x,y;r)$ match in time t this can be estimated by

$$\overline{V}_t^r(x,y) = \log\left[1+\Lambda_t^r(x,y)\right]. \tag{19}$$

Initial match-formation cost is obtained by plugging in the expression for $\overline{V}_t^r(x,y)$ into Equation 14

$$w_t^r(x,y) = \overline{V}_t^r(x,y) - \Phi_t^r(x,y) \tag{20}$$

$$= \log\left[\left(1+\Lambda_t^r(x,y)\right)\frac{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)}{\hat{\mu}_t^r(x,y)^2}\right]. \tag{21}$$

Equation 21 has a meaningful behavioural interpretation. Essentially, one can think of this as being the expected match value being scaled by the ratio of the number of individuals who remained single to the number of new couples. When $\hat{\mu}_t^r(x,y)^2 > \hat{\mu}_t(x,0)\hat{\mu}_t(0,y)$ this implies the formation cost is less than the expected match value and this should induce many new

matches. If the opposite is true, the formation costs will exceed expected match value and matches will only form if individuals experience large idiosyncratic shocks. As one would expect in the limit and holding the separation rate fixed, $w_t^r(x,y) \to 0$ as $\hat{\mu}_t^r(x,y)^2 \to \infty$ and both $\hat{\mu}_t(x,0), \hat{\mu}_t(0,y) \to 0$.[8] However, in practice what is observed is that in any given period, $\hat{\mu}_t^r(x,y)^2 < \hat{\mu}_t(x,0)\hat{\mu}_t(0,y)$.

Finally, the cost incurred by transitioning from an $(x,y;r)$ to an $(x,y;r)$ match is given by

$$\begin{aligned} w_t^{M|C}(x,y) &= \overline{V}_t^M(x,y) - \overline{V}_t^C(x,y) + \log \hat{\mu}_t^{C|C}(x,y) - \log \hat{\mu}_t^{M|C}(x,y) \\ &= \log \left[\left(\frac{1+\Lambda_t^M(x,y)}{1+\Lambda_t^C(x,y)} \right) \frac{\hat{\mu}_t^{C|C}(x,y)}{\hat{\mu}_t^{M|C}(x,y)} \right]. \end{aligned} \tag{22}$$

3.7.3 Match-stability parameters

The parameters $\Phi_t^r(x,y)$, $\overline{V}_t^r(x,y)$, $w_t^r(x,y)$, and $w_t^{M|C}(x,y)$ govern how new matches are formed or the extent to which couples transition between C and M. However, couples who are currently matched decide whether to remain matched or separate based on their current match surplus $\pi_t^r(x,y)$ and the match separation costs $\kappa_t^r(x,y)$. One way to think of this is that prior to being matched, agents decide whether to enter a match or stay single based on their expectation of the value of the match $\overline{V}_t^r(x,y)$ net of the costs of forming the match $w_t^r(x,y)$. However, once this match has been formed, the value is realized, and they decide whether to continue the match or separate based on this realized value.

The estimate of the surplus term $\pi_t^r(x,y)$ comes from matches of the type $(x,y;r)$ that form in that period and also dissolve in that same period. Thus, the estimator is simply

$$\pi_t^r(x,y) = \log\left(1 + \hat{\Lambda}_t^r(x,y)\right)$$

where

$$\hat{\Lambda}_t^r(x,y) = \log\left(\frac{1-\hat{\hat{\delta}}_t^r(x,y)}{\hat{\hat{\delta}}_t^r(x,y)}\right) \tag{23}$$

is the inverse log odds for immediate separations. Thus, the separation cost is given by

$$\kappa_t^r(x,y) = \Lambda_t^r(x,y) - \hat{\Lambda}_t^r(x,y). \tag{24}$$

[8] The number of people who remain single will mechanically go to zero as the number of new matches grows arbitrarily large. These quantities don't move independently.

3.7.4 Male bargaining share

The bargaining share

$$\theta_t^r(x,y) = \frac{\log \hat{\mu}_t^r(x,y) - \log \hat{\mu}_t(x,0)}{2\log \hat{\mu}_t^r(x,y) - \log \hat{\mu}_t(x,0) - \log \hat{\mu}_t(0,y)}.$$

is obtained by manipulating Equation 15. The following Lemma points out a few interesting properties of the bargaining share.

Lemma 1. *Suppose one may change the number of individuals who remain single or become matched while holding the other quantities fixed. In this case, the share of the surplus going to the male is such that*

$$\lim_{\hat{\mu}_t(x,0)\to\infty} \theta_t^r(x,y) = 1, \quad \lim_{\hat{\mu}_t(x,y)\to\infty} \theta_t^r(x,y) = \frac{1}{2}$$

and

$$\begin{aligned}
\frac{\partial \theta_t^r(x,y)}{\partial \hat{\mu}_t(x,0)} &> 0 \text{ if } \hat{\mu}_t(0,y) > \hat{\mu}_t^r(x,y) \\
\frac{\partial \theta_t^r(x,y)}{\partial \hat{\mu}_t(x,0)} &< 0 \text{ if } \hat{\mu}_t(0,y) < \hat{\mu}_t^r(x,y) \\
\frac{\partial \theta_t^r(x,y)}{\partial \hat{\mu}_t(x,0)} &= 0 \text{ if } \hat{\mu}_t(0,y) = \hat{\mu}_t^r(x,y).
\end{aligned}$$

Proof. See Appendix (A.4). □ □

Lemma 1 shows that the share of the surplus going to the male depends on several factors which are determined endogenously in the model. However, somewhat surprisingly, as the number of males who choose to remain single gets arbitrarily large, the bargaining share tends to one, implying the males get all of the surplus. One would think that this should be the other way around. A way to think of this is that, when more males want to remain single, women must incentivize them to match by offering them a larger share and vice versa. However, as Lemma 1 implies, this is only the case when the number of women who remain single exceeds the number of matches that occur. In a world where forming an $(x, y; r)$ match is much more common, this conclusion reverses and instead scarcity on the market improves a male's bargaining share. That is, one's bargaining power also depends on the frequency at which matches occur, not just the number of singles available on the market.

4 Data

The analysis draws on the U.S. Current Population Survey (CPS), accessed via IPUMS (Flood, 2024). The CPS is a monthly labour-force survey that also includes rich demographic information on individuals and households. Each household is interviewed for four consecutive months, leaves the sample for eight months, and then re-enters for another four months before permanently exiting. This 4-8-4 rotation design allows me to observe individuals at two points roughly one year apart, which provides a natural window for measuring transitions in household formation—such as entering or exiting a marriage or cohabitation—on a year-over-year basis. For example, a household observed in January 2008 reappears in January 2009, enabling me to detect whether relationship status changed during the intervening year. Given this structure, I define one model period to correspond to a calendar year. I use nearly the full set of available data, spanning 1983–2023, and exclude earlier years (1976–1982) due to limitations in linking individuals across survey waves. Flood et al. (2022) provide additional discussion of these linkage issues and the methodology used to match respondents within households over time.

	Total	Single	Married	Cohabiting
N	19187141	8571296	9108891	1113120
Age	29.31	26.25	32.29	28.67
% High School	0.47	0.48	0.44	0.51
% Some College	0.29	0.33	0.26	0.27
% College Degree	0.17	0.14	0.20	0.16
% Advanced Degree	0.07	0.05	0.10	0.05
% White	0.82	0.77	0.87	0.83
% Black	0.11	0.15	0.07	0.10
% Asian	0.04	0.04	0.04	0.03
% Hispanic	0.13	0.13	0.13	0.12
% Parents	0.46	0.16	0.76	0.34
# Children	0.93	0.29	1.57	0.60

Table 1: Summary statistics, CPS 1983–2023, ages 18–40

Table 1 presents descriptive statistics for individuals aged 18–40 over the period 1983–2023. In the estimation, I group educational attainment into two categories: "low education" (high school or some college) and "high education" (college or advanced degree). Roughly three-quarters of the sample are low-education types, and one-quarter are high-education types. Reported race categories do not sum to one because respondents can identify with multiple races. Individuals are further classified into four age groups (18–24, 25–29, 30–34, and 35–39) to capture life-cycle differences in partnership behaviour. These summary statistics reveal

several well-known empirical patterns: married individuals are more likely to hold a college degree, to be white, and to have children than those who are single or cohabiting. About 46 percent of the total sample are parents, and among these, nearly 80 percent are married. As shown earlier in Figure B.2, this share has declined steadily over time, consistent with the broader retreat from marriage documented in Section 5.

4.1 Historical cohabitation rates

Measuring cohabitation accurately in the CPS poses additional challenges. Before 2007, the survey did not explicitly ask whether respondents were living with a cohabiting partner. From 1995–2006, it included an "unmarried partner" (UP) category, but as Kennedy and Fitch (2012) show, this item was frequently misunderstood, leading many cohabiting couples not to select it. Prior to 1995, no such field existed, and researchers instead relied on the heuristic of "persons of opposite sex sharing living quarters" (POSSLQ). Like the UP flag, this proxy systematically miscounted cohabiting households, sometimes undercounting and sometimes overcounting depending on changing household composition and sample definitions.[9] Consequently, pre-2007 measures of cohabitation are noisy and inconsistent across time.

Cohabitation itself is also conceptually ambiguous. Unlike marriage, it lacks a formal legal definition in the United States, and common-law marriage is rare.[10] The CPS asks respondents: "Do you have a boyfriend, girlfriend, or partner in this household?" Responses depend partly on interpretation. A small number of respondents report being both married and cohabiting with the same partner; these cases are coded as married but not cohabiting. Others claim to be cohabiting despite no partner being present in the household; these are reclassified as single. To construct a consistent measure of cohabitation across years, I use a deep-learning model trained on post-2007 data, described in Appendix C.1, to predict cohabitation status retrospectively and recover historical rates from 1983 onward.

4.2 Limitations

The CPS provides exceptional temporal coverage and detailed demographic information, but several limitations are important for interpreting the analysis. First, the survey does not contain complete marital or cohabitation histories. While current marital status and

[9] It is not obvious ex ante whether POSSLQ would undercount or overcount cohabitation. Early in the period it appears to overcount, later to undercount, reflecting shifts in the prevalence of multigenerational households and shared living arrangements.

[10] In contrast, common-law unions are widely recognized in Canada, where couples are considered common-law after cohabiting for a specified period—though the threshold varies by province.

indicators for divorce are observed, earlier cohabitations, remarriages, or the sequencing of partnerships are not. As a result, it is not possible to reconstruct entire life-cycle trajectories or to observe repeated transitions between partnership states. This restriction, however, is not problematic for my purposes. The empirical strategy focuses on short-run transitions—such as whether an individual forms, maintains, or dissolves a union between survey years—which the CPS captures accurately through its year-to-year rotation design.

A second limitation concerns the absence of direct information on match duration. The CPS does not report when a relationship began, which means that the exact length of each marriage or cohabitation cannot be observed. Duration can, in principle, be inferred indirectly from other demographic information: for example, Chiappori et al. (2018) show that marriage duration is strongly correlated with age, and the age of children in the household can serve as a proxy for the timing of union formation. In my reduced-form estimation framework, however, explicit duration measures are not required, because identification relies on observed flows between partnership states rather than on full histories. Nonetheless, duration information could be incorporated in future extensions that seek to model agents' forward-looking expectations more structurally—for instance, by linking beliefs about future stability to the expected remaining length of a match.

Finally, linkage across CPS samples is probabilistic rather than deterministic. Because individuals lack unique longitudinal identifiers, IPUMS applies a probabilistic matching algorithm to connect respondents across months and survey years (Flood et al., 2022). The procedure performs well overall, but linkage accuracy is weaker for certain years—most notably 1984–1985 and 1994–1995—when major survey redesigns occurred (Rivera Drew et al., 2014). This feature introduces some uncertainty about whether an individual observed at two dates is indeed the same person, particularly for short-term movers or those in complex households. The results should therefore be interpreted as characterizing transitions among the reliably linked population, rather than as complete longitudinal trajectories for all CPS respondents.

4.3 Construction of dissolution rates and match formation counts

To estimate the structural parameters of the model, I construct annual measures of match formation and dissolution for each arrangement $r \in \mathcal{R}$ and type pair $(x, y) \in \mathcal{Z}$. Each CPS household is observed for four consecutive months, exits for eight months, and then re-enters for four additional months before permanently leaving the sample. This rotation pattern makes it possible to link individuals who appear in the same calendar month one year apart—for example, those interviewed in January 2008 and again in January 2009—and

to observe changes in their relationship status. Using the IPUMS linkage keys, I identify the subset of respondents who persist between the two periods and track transitions in and out of marriage and cohabitation. Formally, for each year–month pair $t = (yr, mth)$, the matched sample at t' corresponds to $(yr + 1, mth)$, allowing me to define annual transitions for all individuals who can be reliably linked.

Let $\mathcal{P}_t^m = (\mathcal{I}_t \cap \mathcal{I}_{t'})$ denote the set of men who persist across consecutive surveys, and $\mathcal{P}_t^w = (\mathcal{J}_t \cap \mathcal{J}_{t'})$ the analogous set of women. The subset of matched couples who persist as pairs is given by $\mathcal{P}_t^{mw} = \{(i,j) \in \mathcal{P}_t^m \cup \mathcal{P}_t^w : (i,j) \text{ are matched at time } t\}$. I then measure dissolution as the share of couples in $(x, y; r)$ matches at t who are no longer matched in t'. For a given individual i, let $\mathbf{1}\{d_{i,t,t'}^r(x,y)\}$ indicate that their relationship status changes from matched to single between t and t', and $\mathbf{1}\{\mu_{i,t,t'}^r(x,y)\}$ that they were matched at the start of the period. The empirical dissolution rate is computed as

$$\hat{\delta}_t^r(x,y) = \frac{\sum_{i\in\mathcal{P}_t^m} \mathbf{1}\{d_{i,t,t'}^r(x,y)\}}{\sum_{i\in\mathcal{P}_t^m} \mathbf{1}\{\mu_{i,t,t'}^r(x,y)\}} + \frac{\sum_{j\in\mathcal{P}_t^w} \mathbf{1}\{d_{j,t,t'}^r(x,y)\}}{\sum_{j\in\mathcal{P}_t^w} \mathbf{1}\{\mu_{j,t,t'}^r(x,y)\}} - \frac{\sum_{(i,j)\in\mathcal{P}_t^{mw}} \mathbf{1}\{d_{i,t,t'}^r(x,y)\}\mathbf{1}\{d_{j,t,t'}^r(x,y)\}}{\sum_{(i,j)\in\mathcal{P}_t^{mw}} \mathbf{1}\{\mu_{i,j,t,t'}^r(x,y)\}}, \tag{25}$$

where the final term corrects for double-counting when both members of a couple remain in the sample.[11]

The same logic applies to match formation. Among the persisted set, I observe who transitions from single to matched between t and t', as well as the characteristics of the new partner. This allows me to construct $\hat{\mu}_t^r(x,y)$, the count of new $(x, y; r)$ matches formed during year t. Double-counting is again addressed by treating couples who transition jointly—for instance, from cohabitation to marriage—as a single formation event. Together, these measures produce annual flow data that can be mapped directly into the models dynamic matching functions, linking observed transitions to estimated formation and dissolution probabilities.

One limitation of this approach is that only individuals who persist across consecutive survey years contribute to these flow estimates. Households drop out of the CPS for several reasons, including relocation or dissolution followed by both partners moving away from the original address. The identifying assumption is therefore that the transition behaviour of those who remain is representative of the population as a whole. While this assumption cannot be verified directly, the use of IPUMS linking weights mitigates bias from differential attrition. Finally, because match dissolutions are relatively infrequent, the raw transition rates can be noisy from year to year. To address this, I apply a non-parametric smoothing procedure

[11] Ignoring the double-counting correction would effectively double the number of observed dissolutions; equivalently, $\hat{\delta}_t^r(x,y)$ could be estimated by regressing the dissolution indicator on a complete set of year and type dummies and taking fitted values.

to the estimated hazards before using them in estimation; details of this procedure and the smoothed series are provided in Appendix C.3.

5 Results

In this section, I present both reduced-form analyses and structural parameter estimates obtained using the non-parametric estimators introduced in Section 3.7. The discussion proceeds in three parts. First, I examine how the parameters governing match formation and dissolution have evolved over the past four decades, distinguishing between marriage and cohabitation. This analysis directly revisits the questions raised in Section 3.1: given that relationships today are more stable but less common, are these patterns driven by rising barriers to entry, barriers to exit, or both? I find that the contemporary low-match-rate regime is primarily the result of higher entry costs, especially among individuals with lower levels of education. This pattern holds for both marriage and cohabitation and helps explain the persistent decline in household formation documented in Fact 1.

To rationalize the increased stability of existing matches in Fact 2, I then examine how match surplus and dissolution costs have changed over time. For marriage, dissolution costs have remained largely stable while per-period surplus has risen modestly, implying that greater marital stability primarily reflects higher intrinsic returns to marriage rather than stronger exit barriers. The change is quantitatively small—divorce rates have fallen by roughly one percentage point over the last forty years—but nonetheless consistent with the steady decline in divorce hazards shown in Figure 2a. For cohabitation, by contrast, the decline in separations has been striking: the one-year dissolution hazard has fallen from about 40% in 1983 to below 20% today (Figure 2b). This pronounced shift could, in principle, stem from either rising surplus or higher separation costs. The estimates indicate that both have increased, suggesting that the growing durability of cohabiting unions reflects not just institutional or financial constraints but also deeper changes in the perceived value of cohabitation. A parallel analysis using age-based types, presented in Appendix B.5, yields qualitatively similar conclusions.

The next two subsections focus on the key inflection points highlighted in Fact 3. Section 5.2 examines the 1990s, when marriage rates fell, cohabitation became more prevalent, and fertility outside marriage rose. I relate these shifts to contemporaneous policy reforms—notably the expansion of paternity establishment and welfare changes affecting unmarried parents—and show that the model can rationalize the resulting shifts in match formation and surplus. Although I do not estimate the causal impact of these policies directly, the models

ability to reproduce the observed changes provides a useful validation of its structure. For causal analyses of these reforms, see Rossin-Slater (2017).

Finally, Section 5.3 turns to the post-2008 period, exploring how changes in asset accumulation and the cost of living have influenced household formation. Following Lafortune and Low (2017) and Lafortune and Low (2023), I document that homeownership has long been positively associated with marriage formation. For much of the last forty years, marriage rates among homeowners exceeded those of renters, consistent with the role of housing as both a financial and commitment asset. The Great Recession, however, altered this relationship: since 2008, the gap in marriage rates between homeowners and renters has narrowed substantially. In contrast to the 20th-century pattern of an uneven retreat from marriage by housing status, all groups have become less likely to form new partnerships regardless of ownership. This pervasive decline motivates my exploration of how rising housing costs—and, more broadly, the increasing cost of living—shape household formation in the contemporary U.S. marriage market.

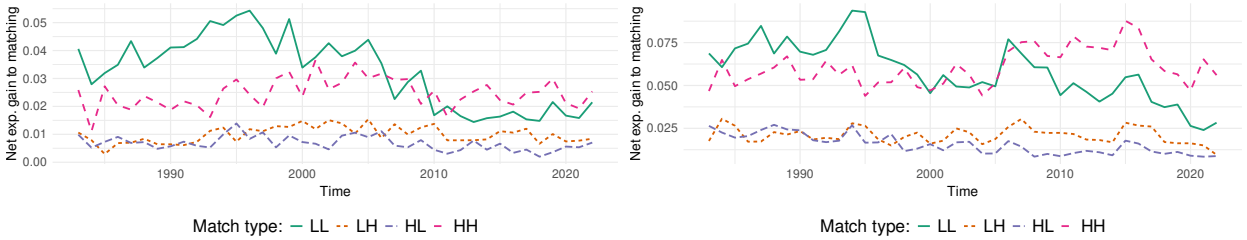
5.1 Trends in matching by education level: the last 40 years

This subsection provides a high-level overview of how the Second Demographic Transition (SDT) has evolved over the past forty years. The analysis addresses the questions posed in Section 3.1: given that relationships have become more stable yet less common, are these patterns driven by rising barriers to entry, barriers to exit, or both? The type space considered here consists of high (H) and low (L) educational categories as defined in Section 4. Each figure plots the estimated structural parameters by year t for all possible (x, y) match types, where $(x, y) \in \{LL, LH, HL, HH\}$. The first letter denotes the mans education type and the second the womans. For instance, an LH match is one between a low-education man and a high-education woman. Fertility is not included in this section—it is introduced in Sections 5.2 and 5.3. Since the analysis is based on educational categories, the sample is restricted to individuals aged 24–40.

5.1.1 Changes in match-formation parameters

I begin with the parameters that determine whether new matches form. Figure 6 displays the net return to matching, $\Phi_t^r(x, y)$, while Figures 7 and 8 show its components—expected match value $\overline{V}_t^r(x, y)$ and formation costs $w_t^r(x, y)$. Together, these parameters explain Fact 1: the long-run decline in new marriages and the rise of cohabitation. For comparison, Appendix B.2 reports static estimates of match surplus using the Choo and Siow (2006) framework. The static surplus is the analogue of $\Phi_t^r(x, y)$ in a stationary environment and

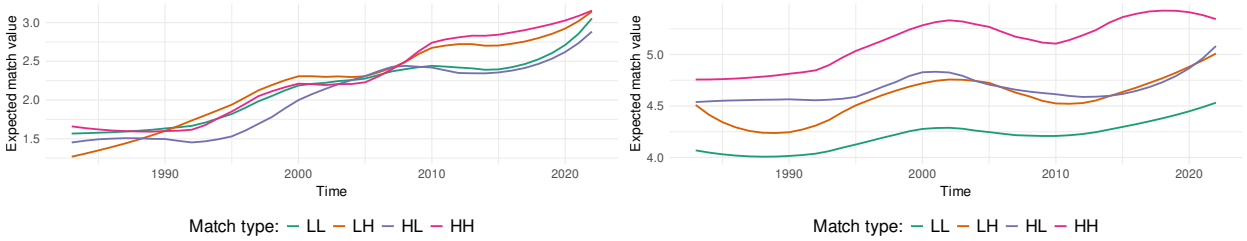
can be interpreted as the flow-based counterpart derived from stocks rather than transitions.



(a) Cohabitation (b) Marriage

Figure 6: Net return to matching $\Phi_t^r(x, y)$

In Figure 6a, the net return to cohabitation remains relatively low for heterogamous types (LH, HL) throughout the sample period, but the homogamous types display notable dynamics. For LL couples, the return to cohabitation rises sharply in the early 1990s, peaks mid-decade, and declines after 2008. For HH couples, returns increase steadily until 2008 before levelling off. The pattern for marriage, shown in Figure 6b, mirrors well-documented trends in the literature (e.g. Lundberg et al., 2016; Chambers et al., 2025): the gains to marriage have remained persistently high for HH types and have fallen substantially for LL types. These results also replicate the finding of Chambers et al. (2025) that match types involving highly educated women have changed the least over time. Because $\Phi_t^r(x, y) = \overline{V}_t^r(x, y) - w_t^r(x, y)$, the next step is to disentangle whether these changes arise from shifts in expected match value, formation costs, or both.

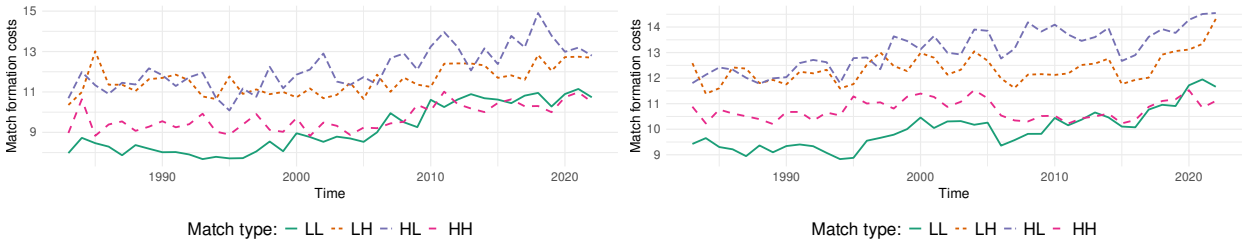


(a) Cohabitation (b) Marriage

Figure 7: Expected match value $\overline{V}_t^r(x, y)$

Expected match value, shown in Figure 7, rises over time for both cohabitation and marriage across all education groups. This reflects the general increase in match stability documented in Section 4. For cohabitation, the differences between education groups are small but inversely related to male education: couples with low-education men exhibit slightly higher match values. This suggests that for lower-education couples, cohabitation functions more as a substitute for marriage rather than a temporary arrangement. The pattern is

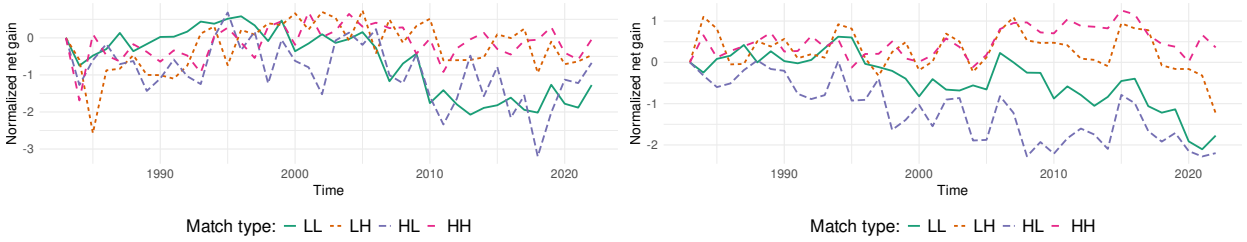
reversed for marriage, where the highest match values are observed among HH couples and the lowest among LL. Moreover, the levels differ markedly—marriage is roughly twice as valuable as cohabitation on average—consistent with the interpretation of marriage as a higher-commitment arrangement with larger expected returns.



(a) Cohabitation (b) Marriage

Figure 8: Match-formation costs $w_t^r(x, y)$

Formation costs, reported in Figure 8, reveal a contrasting pattern. In both marriage and cohabitation, homogamous matches (LL, HH) exhibit the lowest costs, consistent with the idea that search and coordination are easier among similar partners (Ciscato, 2024). These costs capture both monetary and non-monetary components of forming a household—including search, moving, and in the case of marriage, the direct costs of a wedding. Until recently, formation costs were lowest for LL couples, but since the early 2000s they have risen sharply, especially after 2008. HH couples, by contrast, have seen little change in formation costs, which helps explain their persistently higher match rates (see Figure 1a).



(a) Cohabitation (b) Marriage

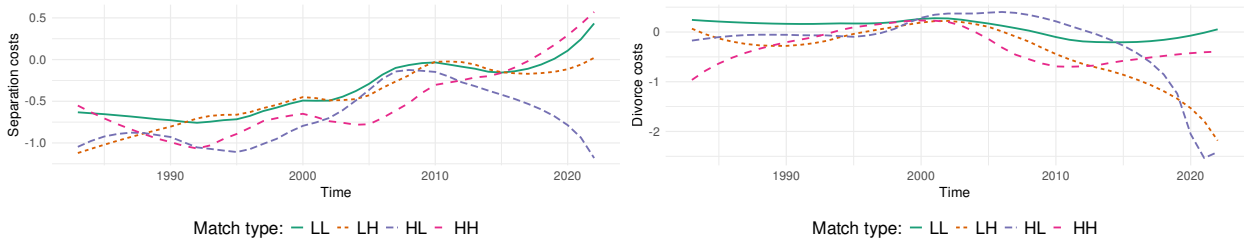
Figure 9: Net returns adjusted such that $\Phi_{1983}^r(x, y) = 0$

To summarize these dynamics more directly, Figure 9 plots net returns adjusted so that $\Phi_{1983}^r(x, y) = 0$. Negative values in later years indicate that a given match type is less likely to form than in 1983. This metric can also be interpreted as the change in the size of the idiosyncratic preference shock required to induce matching in the discrete-choice framework of Equation (9). For instance, forming a HL marriage today requires a much larger idiosyncratic shock than forty years ago because $w_t^M(H, L)$ has risen faster than $\overline{V}_t^M(H, L)$.

Displaying the parameters in this way clearly illustrates the mechanism behind Fact 1: declining match rates stem primarily from rising formation costs, especially among LL and HL couples. While expected match values have increased, the rate of growth has been outpaced by the escalation in entry costs.

Two additional observations are worth emphasizing. First, the two inflection points identified in Fact 3 are visible in both panels of Figure 9, and they are largely driven by shifts in the matching behaviour of low-education women. In the cohabitation panel, formation costs and expected values for LL and HL pairs diverge sharply following the 2008 financial crisis, while in marriage this divergence begins in the mid-1990s. These patterns align with Chambers et al. (2025), who show that low-education women have experienced the largest declines in matching opportunities. Second, my estimates suggest that this is due to formation costs rising faster than the perceived value of matching, effectively crowding certain groups out of both the marriage and cohabitation markets. Interestingly, low-education men appear least affected by these changes—a result that runs counter to the "marriageable men hypothesis," which attributes the decline in marriage among less-educated groups to a shortage of economically viable male partners.[12] As shown in Appendix B.3, this pattern persists even after conditioning on employment status, indicating that declining match formation among low-education groups is not solely a labour-market phenomenon.

5.1.2 Changes in match-stability parameters



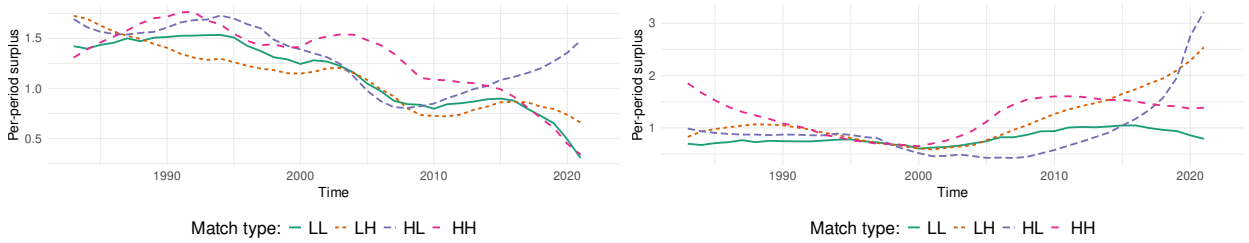
(a) Cohabitation (b) Marriage

Figure 10: Match-dissolution costs $\kappa_t^r(x, y)$

The parameters in Figure 10 are estimated using Equation 24, under the assumption that matches forming and dissolving within the same period do not incur separation costs. As discussed in Section 3.6, this identifying restriction allows the model to disentangle dissolution costs from surplus, making it possible to recover both objects separately. Examining cohabitation first, dissolution costs are consistently highest for the low-education male types

[12] https://ifstudies.org/blog/education-income-and-marriageable-men

(LL and LH) and have increased steadily for all groups over time. In contrast, the marriage estimates in Figure 10b show a much tighter clustering across types and little secular change since the early 1980s. This stability is consistent with the descriptive evidence in Figure 2a, where the divorce hazard exhibits only a modest long-run decline. Cohabitation, by comparison, has experienced a pronounced reduction in separations, implying a meaningful upward trend in match-stability parameters. The greater heterogeneity and upward drift in $\kappa_t^r(x, y)$ for cohabitation thus reflect the evolving persistence of these unions over the second demographic transition.



(a) Cohabitation (b) Marriage

Figure 11: Systematic surplus $\pi_t^r(x, y)$

Alongside dissolution costs, the systematic surplus estimates $\pi_t^r(x, y)$—shown in Figure 11—capture the overall payoff to remaining in a match, combining current and expected future utilities. These are reduced-form objects in the sense that they aggregate both contemporaneous and discounted future surplus, yet they remain the relevant decision variable for couples determining whether to remain together. Owing to data limitations, I cannot separately identify the per-period component $S_t^r(x, y)$ without imposing additional structure, but the evolution of $\pi_t^r(x, y)$ still reveals important behavioural changes.

The estimated surplus values rise over time for all cohabiting match types, indicating that the increased stability of cohabitation is not driven solely by higher exit barriers but also by greater enjoyment of the match itself. In other words, both the carrot (higher surplus) and the stick (higher dissolution costs) have contributed to the persistence of cohabiting unions. For marriage, the pattern is similar in direction but far more muted: systematic surplus has increased slightly across the sample period, while dissolution costs have remained largely unchanged. This contrast reflects the broader stability of marriage hazards relative to the dramatic decline in cohabitation separations. Taken together, these results explain Fact 2: the growing stability of unions arises from a combination of rising surplus and higher dissolution costs for cohabitation, whereas for marriage the effect is driven almost entirely by modest gains in surplus. It is therefore not the case that couples are simply trapped

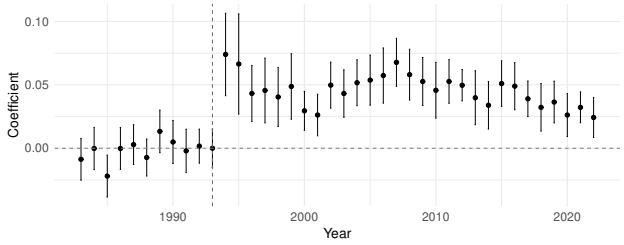
in relationships by prohibitive exit costs; rather, couples today appear both to enjoy their partnerships more and, in the case of cohabitation, to face greater barriers to exit. The next two subsections turn to Fact 3, analysing the inflection points in household formation that occur during the mid-1990s and the post-2008 period.

5.2 The first inflection point: changes in the 1990s

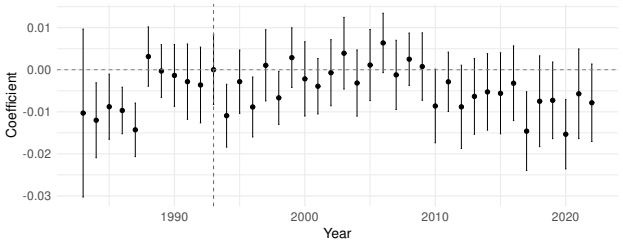
As outlined in Fact 3 and illustrated in Figure 3, there are two clear breaks in U.S. household-formation patterns over the last 40 years. The first occurs in the mid-1990s and is especially visible in Figure 9, where low-education matches (LL and HL) become markedly less likely to marry. In this subsection I examine that first episode more closely by bringing in fertility. The central pattern that emerges is a substitution away from marriage and toward cohabitation, concentrated among couples with children. This timing coincides with a sequence of policy changes in the 1990s that made it easier to establish paternity outside marriage and altered incentives for single mothers to formalize unions. I summarize these policies in Appendix D. Rossin-Slater (2017) shows causally that in-hospital voluntary paternity establishment (IHVPE) increased paternal acknowledgement for non-marital births and reduced marriage among unmarried parents; although I do not estimate causal effects here, the model reproduces the same qualitative implications, which serves as a useful validation exercise.

Figure 12 makes three facts clear. First, once 1993 is taken as the policy anchor year, there is a sharp increase in the one-year fertility hazard for cohabiting couples (Figure 12a), but no corresponding increase for married couples (Figure 12b). This pattern is exactly what we would expect if paternity establishment for non-marital births was suddenly recorded more completely, not if overall fertility was rising. Second, the marriage-linked fertility hazard is flat through this period, which rules out a general baby boom. Third, and most important for the model, the probability that a cohabiting couple transitions to marriage within a year falls noticeably beginning in the mid-1990s (Figure 12c). In other words, more of the couples with children are staying in cohabitation rather than switching to marriage.

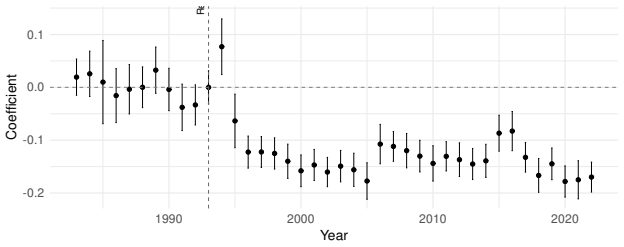
From the models point of view, this drop in cohabitation-to-marriage transitions can arise through two channels. Cohabiting couples solve the discrete choice problem in Equation (11); therefore a lower transition probability can reflect either (i) a fall in the expected value of marriage relative to remaining cohabiting, or (ii) an increase in the switching cost $w_t^{M|C}(x, y)$ that must be paid to convert cohabitation into marriage. Because these costs bundle monetary, legal, and cultural barriers, an increase should be interpreted broadly—for example, if legal recognition of non-marital paternity closes some of the benefits gap between cohabitation and marriage, then the incremental reward to marriage shrinks and a larger idiosyncratic



(a) Fertility hazard: cohabitation



(b) Fertility hazard: marriage

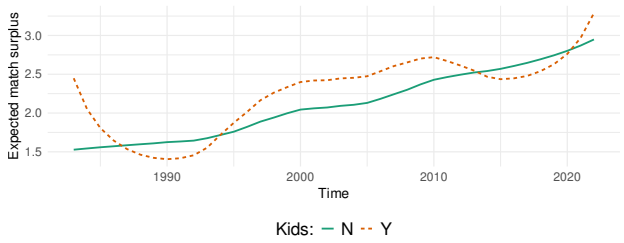


(c) Cohabitation to marriage hazard

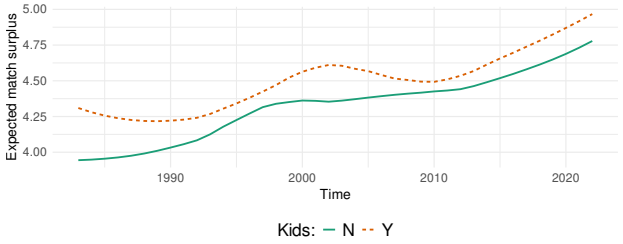
Figure 12: One-year hazards for different events

Notes: Figures show year fixed effects (α_t) from $d_{ist} = \alpha_t + \alpha_s + \beta X_{ist} + \varepsilon_{ist}$, with $t = 1993$ as the reference year. The dependent variable d_{ist} equals one if the event occurred for individual i in state s in the previous 12 months. Controls X_{ist} include education, age, and race dummies. Standard errors clustered at the state level.

shock is required to induce the transition.



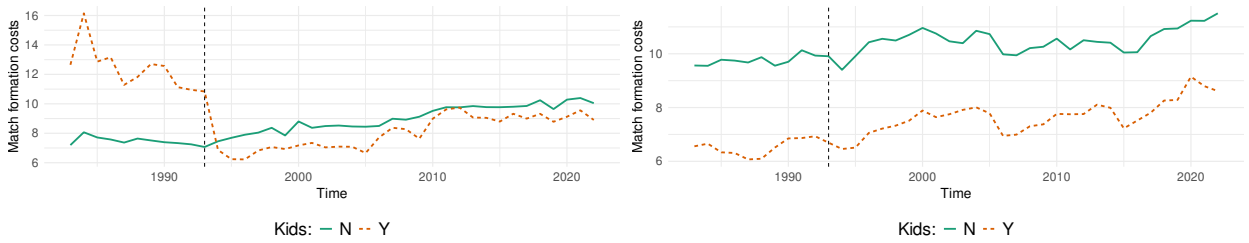
(a) Cohabitation



(b) Marriage

Figure 13: Expected match value by presence of children

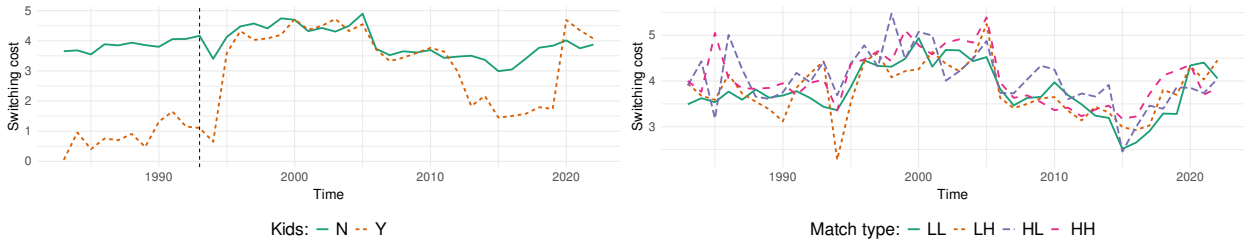
Figures 13 and 14 show that this is precisely what the structural estimates deliver. The model distinguishes two ways a match with children can appear in the data: either parents were non-coresidential and then decide to co-reside (as cohabiters or spouses), or a new coresidential match is formed and a birth occurs within 12 months (see Section 4). Once couples are split in this way, the only parameters that move sharply in the early 1990s are those for cohabiting couples with children. Their expected match value rises relative to childless cohabitors (Figure 13a), which is consistent with children making the existing partnership more valuable once the father is readily recognized. At the same time, their



(a) Cohabitation (b) Marriage

Figure 14: Match-formation costs by presence of children

match-formation costs fall toward those of childless cohabitors (Figure 14a), which is exactly what we would expect if IHVPE removed the extra legal/administrative step that previously made cohabitation with children a more expensive relationship status. Importantly, no analogous break is visible in the marriage series (Figures 13b and 14b), in line with the fact that the 1990s changes targeted non-marital births rather than marriage itself.



(a) Kids vs. no kids (b) Education types

Figure 15: Switching cost: cohabitation to marriage

The final piece of evidence comes from the estimated switching cost from cohabitation to marriage, $w_t^{M|C}(x, y)$, shown in Figure 15. At first glance, the sharp increase in the mid-1990s—especially for couples with children (Figure 15a)—may look counterintuitive. But within this framework, the switching cost is best read as the size of the idiosyncratic push required to justify marriage over staying cohabiting. Once cohabitation is legally and practically closer to marriage, that push must be larger. Put differently, if IHVPE and related policies flatten the cohabitation–marriage gap for parents, then only couples with unusually high marriage-specific utility will marry. Figure 15b shows that this pattern does not vary much by educational attainment; what matters is the presence of children. This lines up cleanly with the event-study evidence in Figure 12c.

What does this imply for Fact 3? It suggests that the first inflection point—the 1990s shift away from marriage toward cohabitation—was driven disproportionately by cohabiting couples with children, for whom the institutional environment made non-marital coresidence

cheaper and marriage less necessary. This is somewhat ironic, given that several of the 1990s reforms were explicitly framed as discouraging non-marital childbearing.[13] Consistent with Rossin-Slater (2017), I find that the reforms coincided with lower transition rates into marriage for unmarried parents. The contribution of the present model is to show, using a flow-based dynamic matching framework, that this shows up exactly where we would expect it to: in lower marriage hazards for cohabiting parents, in lower formation costs for cohabitation with children, and in higher switching costs out of cohabitation. In that sense, the 1990s episode is a useful stress test of the model's ability to separate surplus from costs.

5.3 The second inflection point: post-2008

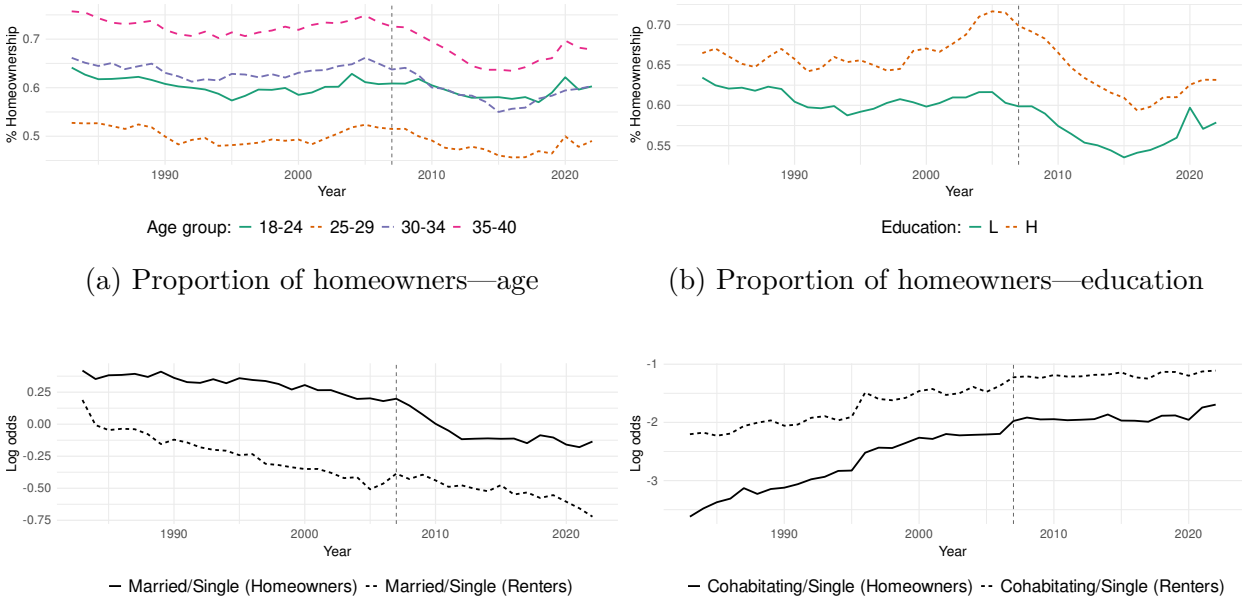
In this subsection I document the second major break in household-formation behaviour that follows the 2008 housing bust, and I relate it to changes in homeownership and housing costs. I first describe the raw facts on homeownership, match rates, and the relative marriage/cohabitation advantage of homeowners. I then connect these facts to the model by asking whether rising post-2008 home prices can be interpreted as higher match-formation costs, and whether this mechanism can explain why matching fell for everyone, not just for renters. Finally, I set up a counterfactual exercise in which I re-simulate matching flows under an alternative house-price path.

5.3.1 Trends in homeownership, match rates, and home prices

There are, of course, multiple reasons why match rates declined so sharply after 2008, but I focus here on the housing channel. This is both empirically salient and well anchored in the literature: Lafortune and Low (2017) and Lafortune and Low (2023) show that housing wealth and homeownership are strongly predictive of marriage, and survey evidence emphasises that young adults frequently cite cost of living as a reason for delaying co-residence or marriage (Wang and Parker, 2014). Because housing costs take up a large share of income for precisely the ages in which matching occurs, interpreting the post-2008 retreat from marriage and cohabitation through the lens of housing prices is natural.[14] Figure 16a shows that homeownership rates fell for all age groups after 2008, with the largest drops for those in their late twenties and thirties. Figure 16b shows a very similar decline across educational groups—college-educated and non-college adults both became less likely to own. So the post-2008 shift is not only an age-composition story and not only a low-education story; it is a broad contraction in access to owner-occupied housing.

[13] See Appendix D for a timeline and discussion.

[14] See, for example, contemporary reporting on rent burdens among young adults: `https://www.marketplace.org/story/2024/10/23/gen-z-is-burdened-by-rent-that-doesnt-bode-well-for-its-future-wealth`



(a) Proportion of homeowners—age

(b) Proportion of homeowners—education

(c) Married log-odds by homeownership

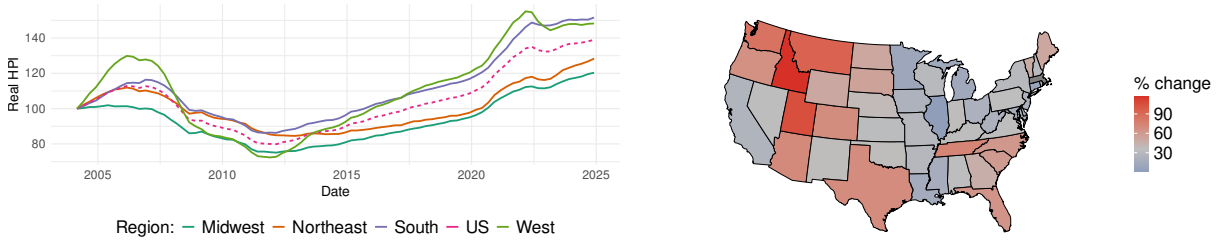
(d) Cohabitation log-odds by homeownership

Figure 16: Homeownership rates and log-odds

What makes this decline in ownership relevant in the context of the second demographic transition is the tight association between homeownership and marriage at the start of the sample. In the 1980s and 1990s, married log-odds for homeowners and non-homeowners were quite close (Figure 16c). Over time, however, a sizeable "marriage gap" opened up: homeowners increasingly displayed higher marriage log-odds than non-homeowners, with the gap peaking right around 2008. In other words, just before the housing crash, being a homeowner was most predictive of being married. After 2008, that gap narrowed slightly—not because renters suddenly married more, but because homeowners married less. In the cohabitation panel (Figure 16d), we see the mirror image where cohabitation is persistently more common among non-homeowners, and the relative advantage of renters in cohabitation is stable throughout. Put together, these figures say that ownership fell for almost everyone, marriage was concentrated among owners just before the crash, and after the crash even owners pulled back from marriage. That is suggest some change in the linkage between household formation and homeownership which could be driven by changes in market conditions—this is what I will explore here.

To connect this to an actual price series, Figure 17a plots the wage-deflated FHFA house-price index (HPI) for 2004–2025 by Census region, normalised to 100 in 2004.[15] All regions

[15]HPI data are from the U.S. Federal Housing Finance Agency; wages used for deflation are from the U.S. Bureau of Labor Statistics.



(a) Region (b) State

Figure 17: Trends in real home prices

experience a sharp drop after 2008 as the housing market collapses. But starting around 2011–2012, real prices begin to rise again, and they do so very quickly in the South and West. Figure 17b confirms this at the state level: over 2004–2024 essentially every state saw positive real HPI growth, with the smallest increases in the Midwest and Northeast and the largest in the South and West.[16] Part of this is pure catch-up—Southern and Western states started from lower levels and are closing the gap with historically more expensive markets—but for household formation what matters is the local, current price level. A 25–35 year-old couple in 2025 in Phoenix, Austin, or Tampa is facing a very different housing budget constraint than an observationally similar couple in 1995 or even 2005.

These descriptive patterns set up the question the model is designed to answer: when an observed state variable like local HPI rises, how much of the subsequent fall in marriage/cohabitation flows should we attribute to an increase in match-formation costs $w_t^r(x, y)$, and how much reflects a genuine decline in expected match value $\overline{V}_t^r(x, y)$ (for example because dual-earner housing risk makes separation more costly)? In the next subsection I show how to use the flow-based estimators from Section 3.7 to discipline this decomposition, and I construct a counterfactual in which house prices follow a flatter path post-2008 to quantify how large the matching slowdown would have been in the absence of the housing boom–bust–recovery sequence.

5.3.2 Empirical strategy

To assess how changes in housing prices shape match-formation behaviour, I restrict the sample to residents of major metropolitan areas.[17] Within this sample, I expand the type

[16] See also the U.S. Census Bureaus recent migration releases for evidence on South/West in-migration: `https://www.census.gov/newsroom/press-releases/2024/population-estimates-international-migration.html`.

[17] See Appendix E for a full description of the sample construction.

space so that x and y denote joint age–education types, and I limit the analysis to individuals aged 24 and older. I then estimate reduced-form relationships between local house prices and the two key structural parameters—expected match value and match-formation cost—using specifications of the form

$$\overline{V}_{ijct}(x,y) = \alpha_t^V + \alpha_c^V + \alpha_{xy}^V + \beta_1^V \, HPI_{tc} + \beta_2^V \, HPI_{tc} \times 1_{xy} + \boldsymbol{\gamma}^{V\prime}\mathbf{Z}_{ijct} + u_{ijct},$$

for individuals i and j in an $(x,y;r)$-type match located in city c during period t. The vector $\mathbf{Z}_{ijct}$ includes individual-level controls, while α_t^V, α_c^V, and α_{xy}^V denote time, city, and match-type fixed effects. I interact local house prices HPI_{tc} with type dummies to allow for heterogeneous responses across education–age groups. An analogous specification is estimated for match-formation costs:

$$w_{ijct}(x,y) = \alpha_t^w + \alpha_c^w + \alpha_{xy}^w + \beta_1^w \, HPI_{tc} + \beta_2^w \, HPI_{tc} \times 1_{xy} + \boldsymbol{\gamma}^{w\prime}\mathbf{Z}_{ijct} + v_{ijct}.$$

These regressions are estimated separately for marriage and cohabitation, and the same structure is applied to transitions between relationship types (e.g., $w_{ijct}^{M|C}(x,y)$). This decomposition illustrates one advantage of the dynamic, flow-based approach: because $\overline{V}_t^r(x,y)$ and $w_t^r(x,y)$ are identified separately, I can examine how housing-market shocks influence both returns to existing matches and barriers to new formation.

For interpretation, consider the coefficients on HPI_{tc}. It is unlikely that the two parameters respond symmetrically: $\beta_1^{\overline{V}}$ need not equal β_1^w. Estimating the effect of housing prices only through the net return $\Phi_t^r(x,y) = \overline{V}_t^r(x,y) - w_t^r(x,y)$ would obscure this heterogeneity.[18] Intuitively, increases in home prices may simultaneously raise the payoff to remaining matched—as ownership becomes more valuable—and raise the cost of forming new unions, since entry into shared housing is more expensive. Formally, we might expect $\beta_1^{\overline{V}} > 0$ and $\beta_1^w > 0$, but the relative magnitudes determine which margin dominates: if $\beta_1^{\overline{V}} > \beta_1^w$, rising prices strengthen match persistence; if $\beta_1^w > \beta_1^{\overline{V}}$, they primarily deter new formation.

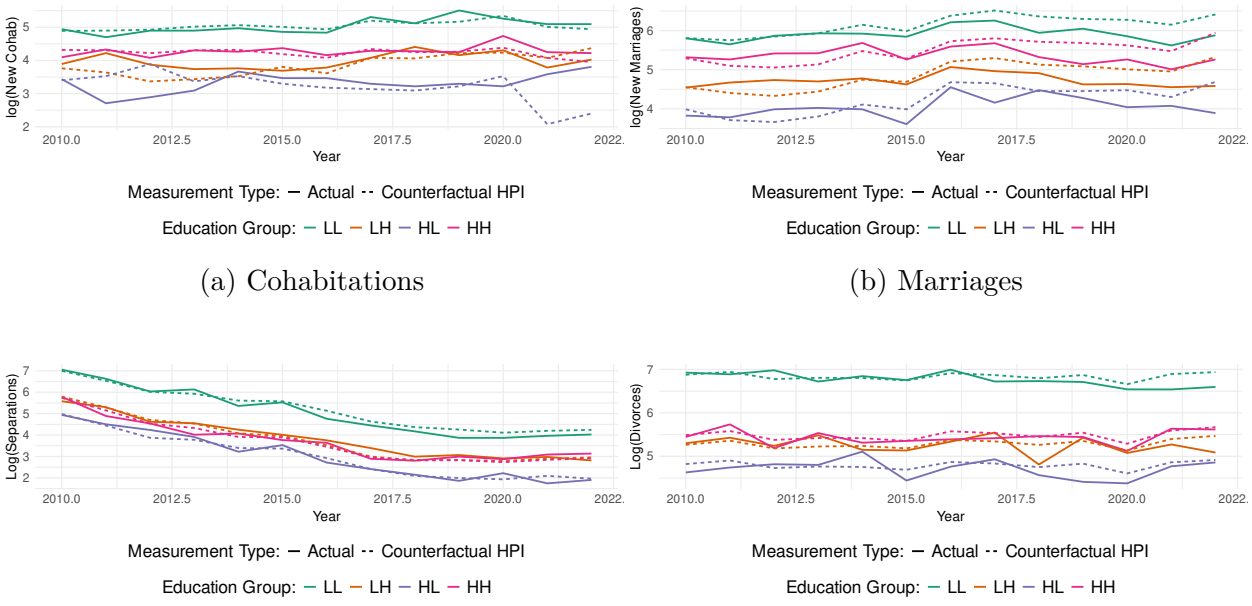
A key concern, however, is that house prices may be endogenous to local economic conditions that also affect relationship decisions. To address this, I employ an instrumental-variables strategy using changes in municipal rent-control policies as an instrument for HPI_{tc}. The instrument is relevant because rent-control regimes are strongly correlated with local hous-

[18] The samples for these two equations also differ: match-formation costs are estimated using newly formed couples, while expected match value is estimated for incumbent matches. Hence, the linearity of OLS does not imply that $\beta_1^{\overline{V}} + \beta_1^w$ equals the coefficient from a regression on the net return.

ing prices, but plausibly exogenous to individual-level matching behaviour. The identifying assumption is that couples do not decide whether to form or dissolve a coresidential relationship based directly on the presence of rent control in their city. While rent control could influence housing supply, potentially violating this assumption, I conduct a robustness check comparing IV estimates across homeowner and renter subsamples and find no evidence of systematic differences. Additional discussion of the instrument and first-stage results is provided in Appendix E.

5.3.3 Counterfactual exercise

To quantify how rising home prices have shaped household formation since the Great Recession, I conduct a counterfactual simulation in which housing prices are held fixed at their 2010 level and a new matching-market equilibrium is recomputed for each subsequent year.[19] The year 2010 serves as a natural benchmark because it marks the nadir of real house prices following the 2008 crash. As shown in Figure 17a, between 2010 and 2024 wage-deflated home prices in the United States rose by roughly 75%. The counterfactual therefore asks: how would matching and dissolution patterns have evolved had this increase not occurred?



(a) Cohabitations

(b) Marriages

(c) Separations

(d) Divorces

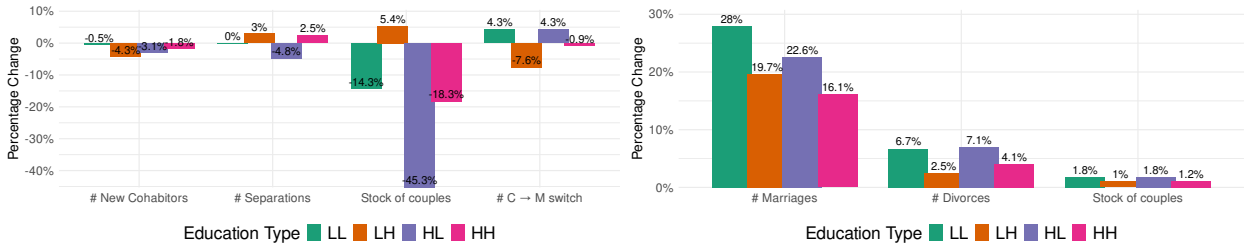
Figure 18: Actual vs. counterfactual household flows under constant 2010 home prices

Figure 18 compares the evolution of household flows under the observed and counterfactual price paths. For cohabitation, changes in home prices have only modest effects on new

[19] Appendix A.5 describes the simulation procedure in detail.

formations: couples appear relatively insensitive to housing costs when forming cohabiting unions. By contrast, marriage formation responds much more strongly. When home prices are fixed at 2010 levels, every educational group displays higher marriage entry, consistent with the interpretation that rising housing costs operate primarily through higher match-formation costs for marriage.

On the dissolution margin, the results mirror those patterns. Higher home prices are associated with fewer separations and divorces, consistent with the view that housing costs increase the price of exit by raising the expense of re-establishing independent housing. As shown in Figure 18d, divorces are marginally more frequent for all education groups under the low-price counterfactual, except among HH couples, who appear insulated from these housing-market constraints. This asymmetry is intuitive: high-income or high-education couples can absorb exit costs more easily, while lower-education couples are more constrained by rising asset prices. For cohabitation (Figure 18c), the same qualitative relationship holds but is less pronounced—still, low-education couples show a measurable response to changing home prices.



(a) Cohabitation

(b) Marriage

Figure 19: Percentage change, 2010–2023: actual vs. counterfactual HPI

Figure 19 summarizes the cumulative effects over 2010–2023 by comparing the stocks implied by each flow series. In cohabitation, fixing home prices has little effect on the number of new unions but produces a modest increase in separations among LH and HH couples. The aggregate stock of cohabiting couples therefore changes little under the counterfactual. For LL couples, however, the counterfactual stock declines, primarily because more cohabitors transition into marriage when housing is cheaper. The HH group experiences a similar reduction, but for the opposite reason: lower home prices modestly raise divorce rates and reduce new formations.

The marriage results are sharper. With prices fixed at 2010 levels, all couple types exhibit substantial increases in new marriages, with the largest proportional gains among LL

couples. At the same time, divorces also rise across types. Because the existing stock of married couples is large relative to the annual inflow of new marriages, even a small increase in divorce offsets much of the rise in formation. Consequently, the net change in the stock of married couples is only modestly positive. This highlights a key feature of equilibrium household dynamics: easing barriers to entry raises formation, but if it also lowers exit costs, the long-run stock response can be muted. Still, the results suggest that lower housing costs—whether through falling prices or increased access to ownership—would lead to higher marriage formation overall, consistent with the interpretation of housing as a binding constraint on modern household formation.

6 Conclusion

This paper develops a dynamic and non-stationary matching framework that helps explain several defining features of the Second Demographic Transition (SDT). Building on the logic of Choo and Siow (2006), I extend the model to include endogenous separation and non-marital cohabitation within a unified flow-based structure. This approach provides a coherent explanation for how household-formation behaviour in the United States has evolved over the past four decades. As Lesthaeghe and Van de Kaa (1986) anticipated, marriage rates have declined steadily since the 1980s, fertility has fallen, and womens educational attainment and labour-force participation have increased. Yet one key prediction of the original SDT hypothesis—that divorce and separation would continue to rise—did not materialize. Instead, divorce rates peaked shortly after the introduction of unilateral divorce laws and have gradually declined ever since. The model rationalizes these facts: increasing match values have made existing unions more stable, while rising formation costs have made new matches harder to initiate. In cohabitation, stability has grown through a combination of higher returns to matching and rising dissolution costs, whereas in marriage, small declines in separation costs have been offset by higher per-period surplus.

The parameter estimates also clarify why cohabitation has become an increasingly attractive alternative to marriage. Forming a cohabiting union entails a lower entry cost and a lower expected exit cost than marriage. As social norms around extramarital fertility have relaxed, the relative attractiveness of cohabitation has increased further. To borrow Nicholas Eberstadts phrase, the modern family system has shifted from long, stable marriages toward increasingly contingent liaisons.[20] Although divorce is less pervasive than that description suggests, it is undeniable that the American household landscape has changed profoundly.

[20] See `https://www.wsj.com/articles/nicholas-eberstadt-the-global-flight-from-the-family-1424476179`.

Young adults today face a matching market in which entry is costlier and coordination more difficult than it was for their parents. After four decades of decline, falling marriage and fertility rates appear not to be a temporary shock but a persistent structural shift. The open question is how far this retreat from traditional household formation will continue.

Beyond documenting long-run trends, the model sheds light on specific mechanisms underlying the observed inflection points. The first occurred in the early 1990s, when policy reforms—including hospital-based paternity establishment and welfare eligibility rules—lowered the costs of non-marital fertility. The model replicates the resulting substitution from marriage to cohabitation among parents and clarifies why cohabiting couples with children became less likely to transition into marriage. The second inflection point emerged after the 2008 financial crisis, when access to homeownership tightened sharply. The analysis suggests that rising housing costs raised match-formation barriers, particularly for those with less education, while modestly reinforcing match stability through higher exit costs. In the counterfactual simulation holding real home prices constant at 2010 levels, the model predicts 1–1.8% more currently married couples relative to the observed outcome, with the largest effects among lower-education groups. These findings highlight that the marriage decline since 2008 is not solely a cultural or educational phenomenon—it also reflects material constraints in the housing market.

Taken together, the results point to a broad reconfiguration of household formation in the United States: marriages are more selective, cohabitations are more durable, and economic barriers have become central in shaping family transitions. The dynamic, flow-based modelling approach developed here provides a flexible foundation for studying these changes, allowing researchers to separate the effects of expected surplus, formation costs, and dissolution costs without imposing strong equilibrium assumptions. Future work could extend this framework to incorporate fertility and asset accumulation directly, or to explore counterfactual policies—such as housing subsidies or childcare support—that could lower entry barriers and alter the trajectory of the SDT in the decades ahead.

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A Theoretical appendix

A.1 Proof of Proposition 1

Couples choose an optimal transfer to solve the Nash bargaining problem

$$\tau_{ijt}^{r*}(x,y;\theta_t^r,\lambda_t^r,\omega_t^r) = \tag{a.1}$$
$$\underset{\tau_{ijt}}{\operatorname{argmax}} \left[\tau_{ijt} + \beta\mathbb{E}V_{i,t+1}^{r'}(x',y';\theta_{t+1}^{r'},\Omega_{t+1}^{r'}) - \left[\beta\mathbb{E}V_{i,t+1}^{S}(x',\varepsilon_{t+1}(x')) - \lambda^r(x,y)\kappa_t^r(x,y)\right]\right]^{\theta_t^r(x,y)} \times$$
$$\left[S_t^r(x,y) + \omega_{ijt}^r - \tau_{ijt} + \beta\mathbb{E}V_{j,t+1}^{r'}(y',x';\theta_{t+1}^{r'},\Omega_{t+1}^{r'}) - \left[\beta\mathbb{E}V_{j,t+1}^{S}(y',\varepsilon_{t+1}(y')) - (1-\lambda^r(x,y))\,\kappa_t^r(x,y)\right]\right]^{1-\theta_t^r(x,y)}.$$

For the sake of notational simplicity, let

$$U_{it}^r(x,y;\theta_t^r,\lambda_t^r,\omega_t^r) \equiv \beta\mathbb{E}V_{i,t+1}^{r'}(x',y';\theta_{t+1}^{r'},\Omega_{t+1}^{r'}) - \left[\beta\mathbb{E}V_{i,t+1}^{S}(x',\varepsilon_{t+1}(x')) - \lambda^r(x,y)\kappa_t^r(x,y)\right]$$

and

$$U_{jt}^r(y,x;\theta_t^r,\lambda_t^r,\omega_t^r) \equiv S_t^r(x,y) + \omega_{ijt}^r + \beta\mathbb{E}V_{j,t+1}^{r'}(y',x';\theta_{t+1}^{r'},\Omega_{t+1}^{r'}) - \left[\beta\mathbb{E}V_{j,t+1}^{S}(y',\varepsilon_{t+1}(y')) - (1-\lambda^r(x,y))\,\kappa_t^r(x,y)\right].$$

The bargaining problem can be rewritten as

$$\tau_{ijt}^{r*}(x,y;\theta_t^r,\lambda_t^r,\omega_t^r) = \underset{\tau_{ijt}}{\operatorname{argmax}} \left[\tau_{ijt} + U_{it}^r(x,y;\theta_t^r,\lambda_t^r,\omega_t^r)\right]^{\theta_t^r(x,y)} \left[U_{jt}^r(y,x;\theta_t^r,\lambda_t^r,\omega_t^r) - \tau_{ijt}\right]^{1-\theta_t^r(x,y)}. \tag{a.2}$$

Taking the first-order condition w.r.t. τ_{ijt} and setting it equal to zero provides

$$\begin{aligned}
&\frac{\partial}{\partial\tau_{ijt}} \left[\tau_{ijt} + U_{it}^r(x,y;\theta_t^r,\lambda_t^r,\omega_t^r)\right]^{\theta_t^r(x,y)} \left[U_{jt}^r(y,x;\theta_t^r,\lambda_t^r,\omega_t^r) - \tau_{ijt}\right]^{1-\theta_t^r(x,y)} \\
&= \theta_t^r(x,y) \left[\tau_{ijt} + U_{it}^r(x,y;\theta_t^r,\lambda_t^r,\omega_t^r)\right]^{\theta_t^r(x,y)-1} \left[U_{jt}^r(y,x;\theta_t^r,\lambda_t^r,\omega_t^r) - \tau_{ijt}\right]^{1-\theta_t^r(x,y)} \\
&- (1-\theta_t^r(x,y)) \left[\tau_{ijt} + U_{it}^r(x,y;\theta_t^r,\lambda_t^r,\omega_t^r)\right]^{\theta_t^r(x,y)} \left[U_{jt}^r(y,x;\theta_t^r,\lambda_t^r,\omega_t^r) - \tau_{ijt}\right]^{-\theta_t^r(x,y)(x,y)} \\
&= 0
\end{aligned}$$

This can be rearranged to obtain

$$\begin{aligned}
&\theta_t^r(x,y) \left[\tau_{ijt} + U_{it}^r(x,y;\theta_t^r,\lambda_t^r,\omega_t^r)\right]^{\theta_t^r(x,y)-1} \left[U_{jt}^r(y,x;\theta_t^r,\lambda_t^r,\omega_t^r) - \tau_{ijt}\right]^{1-\theta_t^r(x,y)} \\
&= (1-\theta_t^r(x,y)) \left[\tau_{ijt} + U_{it}^r(x,y;\theta_t^r,\lambda_t^r,\omega_t^r)\right]^{\theta_t^r(x,y)} \left[U_{jt}^r(y,x;\theta_t^r,\lambda_t^r,\omega_t^r) - \tau_{ijt}\right]^{-\theta_t^r(x,y)}.
\end{aligned}$$

Dividing both sides by $[\tau_{ijt} + U^r_{it}(x, y; \theta^r_t, \lambda^r_t, \omega^r_t)]^{\theta^r_t(x,y)} [U^r_{it}(x, y; \theta^r_t, \lambda^r_t, \omega^r_t) - \tau_{ijt}]^{-\theta^r_t(x,y)}$ and a bit of manipulation provides

$$\begin{aligned}
&\theta^r_t(x, y) [\tau_{ijt} + U^r_{it}(x, y; \theta^r_t, \lambda^r_t, \omega^r_t)]^{-1} \left[U^r_{jt}(y, x; \theta^r_t, \lambda^r_t, \omega^r_t) - \tau_{ijt}\right] = (1 - \theta^r_t(x, y)) \\
\iff &\theta^r_t(x, y) \left[U^r_{jt}(y, x; \theta^r_t, \lambda^r_t, \omega^r_t) - \tau_{ijt}\right] = (1 - \theta^r_t(x, y)) [\tau_{ijt} + U^r_{it}(x, y; \theta^r_t, \lambda^r_t, \omega^r_t)] \\
\iff &\tau^{r*}_{ijt}(x, y; \theta^r_t, \lambda^r_t, \omega^r_t) = \theta^r_t(x, y) U^r_{jt}(y, x; \theta^r_t, \lambda^r_t, \omega^r_t) - (1 - \theta^r_t(x, y)) U^r_{it}(x, y; \theta^r_t, \lambda^r_t, \omega^r_t).
\end{aligned} \tag{a.3}$$

From Equation a.2, the amount going to man i is $\tau_{ijt} + U^r_{it}(x, y; \theta^r_t, \lambda^r_t, \omega^r_t)$. Correspondingly, woman j will get $U^r_{jt}(y, x; \theta^r_t, \lambda^r_t, \omega^r_t) - \tau_{ijt}$. Plugging in the optimal transfer $\tau^{r*}_{ijt}(x, y; \theta^r_t, \lambda^r_t, \omega^r_t)$ from Equation a.3 implies the man receives

$$\begin{aligned}
&\theta^r_t(x, y) U^r_{jt}(y, x; \theta^r_t, \lambda^r_t, \omega^r_t) - (1 - \theta^r_t(x, y)) U^r_{it}(x, y; \theta^r_t, \lambda^r_t, \omega^r_t) + U^r_{it}(x, y; \theta^r_t, \lambda^r_t, \omega^r_t) \\
&\iff \theta^r_t(x, y) U^r_{jt}(y, x; \theta^r_t, \lambda^r_t, \omega^r_t) + \theta^r_t(x, y) U^r_{it}(x, y; \theta^r_t, \lambda^r_t, \omega^r_t).
\end{aligned}$$

Substituting the definitions of $U^r_{jt}(y, x; \theta^r_t, \lambda^r_t, \omega^r_t)$ and $U^r_{it}(x, y; \theta^r_t, \lambda^r_t, \omega^r_t)$ gives

$$\begin{aligned}
&\theta^r_t(x, y) \left(S^r_t(x, y) + \omega^r_{ijt} + \beta \mathbb{E} V^{r'}_{j,t+1}(y', x'; \theta^{r'}_{t+1}, \Omega^{r'}_{t+1}) - \left[\beta \mathbb{E} V^S_{j,t+1}(y', \varepsilon_{t+1}(y')) - (1 - \lambda^r(x, y)) \kappa^r_t(x, y)\right]\right) \\
&+ \theta^r_t(x, y) \left(\beta \mathbb{E} V^{r'}_{i,t+1}(x', y'; \theta^{r'}_{t+1}, \Omega^{r'}_{t+1}) - \left[\beta \mathbb{E} V^S_{i,t+1}(x', \varepsilon_{t+1}(x')) - \lambda^r(x, y) \kappa^r_t(x, y)\right]\right).
\end{aligned}$$

Simplifying the the above expression gives

$$\begin{aligned}
&\theta^r_t(x, y) \left(S^r_t(x, y) + \omega^r_{ijt} + \beta \mathbb{E} V^{r'}_{j,t+1}(y', x'; \theta^{r'}_{t+1}, \Omega^{r'}_{t+1}) - \left[\beta \mathbb{E} V^S_{j,t+1}(y', \varepsilon_{t+1}(y')) - (1 - \lambda^r(x, y)) \kappa^r_t(x, y)\right]\right. \\
&\left. + \beta \mathbb{E} V^{r'}_{j,t+1}(y', x'; \theta^{r'}_{t+1}, \Omega^{r'}_{t+1}) - \left[\beta \mathbb{E} V^S_{j,t+1}(y', \varepsilon_{t+1}(y')) - (1 - \lambda^r(x, y)) \kappa^r_t(x, y)\right]\right)
\end{aligned}$$

or alternatively,

$$\theta^r_t(x, y) V^r_{ijt}(x, y)$$

as claimed. An analogous derivation yields the share of the match value going to woman j

$$[1 - \theta^r_t(x, y)] V^r_{ijt}(x, y).$$

Finally, a match will persist if and only if the sum of the per-period utility and continuation values are greater than the reservation value. Clearly this is equivalent to saying that $V^r_{ijt}(x, y) > 0$.

□

A.2 Proof of Proposition 2

Given the distributional assumptions on the $\boldsymbol{\varepsilon}_{it}(x)$, the probability that a man i of type x in time period t selects a partner of type y in arrangement r as

$$p_t\left(\text{man } i \text{ of type } x \text{ chooses } \{y,r\}\right) = \frac{\exp\left\{\theta_t^r(x,y)\overline{V}_t^r(x,y) - \eta_t^r(x,y)w_t^r(x,y)\right\}}{1+\sum_{\tilde{y}\in\mathcal{Y}}\sum_{\tilde{r}\in\mathcal{R}}\exp\left\{\theta_t^{\tilde{r}}(x,y)\overline{V}_t^{\tilde{r}}(x,y) - \eta_t^{\tilde{r}}(x,y)w_t^{\tilde{r}}(x,y)\right\}}.$$

Similarly, the probability that man i chooses to remain single is given by

$$p_t\left(\text{man } i \text{ of type } x \text{ chooses } \{0\}\right) = \frac{1}{1+\sum_{\tilde{y}\in\mathcal{Y}}\sum_{\tilde{r}\in\mathcal{R}}\exp\left\{\theta_t^{\tilde{r}}(x,y)\overline{V}_t^{\tilde{r}}(x,y) - \eta_t^{\tilde{r}}(x,y)w_t^{\tilde{r}}(x,y)\right\}}.$$

Taking the ratio of these two probabilities we obtain

$$\frac{p_t\left(\text{man } i \text{ of type } x \text{ chooses } \{y,r\}\right)}{p_t\left(\text{man } i \text{ of type } x \text{ chooses } \{0\}\right)} = \exp\left\{\theta_t^r(x,y)\overline{V}_t^r(x,y) - \eta_t^r(x,y)w_t^r(x,y)\right\}.$$

An analogous expression for a woman j of type y is given by

$$\frac{p_t\left(\text{woman } j \text{ of type } y \text{ chooses } \{x,r\}\right)}{p_t\left(\text{woman } j \text{ of type } y \text{ chooses } \{0\}\right)} = \exp\left\{\left[1-\theta_t^r(x,y)\right]\overline{V}_t^r(x,y) - \left[1-\eta_t^r(x,y)\right]w_t^r(x,y)\right\}.$$

By replacing the probabilities with their maximum-likelihood estimates gives us demand for $\{y,r\}$ matches in time t

$$(D): \hat{\mu}_t^{r,d}(x,y) = \hat{\mu}_t(x,0)\exp\left\{\theta_t^r(x,y)\overline{V}_t^r(x,y) - \eta_t^r(x,y)w_t^r(x,y)\right\} \tag{a.4}$$

and supply

$$(S): \hat{\mu}_t^{r,s}(x,y) = \hat{\mu}_t(0,y)\exp\left\{\left[1-\theta_t^r(x,y)\right]\overline{V}_t^r(x,y) - \left[1-\eta_t^r(x,y)\right]w_t^r(x,y)\right\} \tag{a.5}$$

In a marriage market equilibrium $\theta_t^r(x,y)$ will recalibrate such that $(D) = (S)$. Setting $\hat{\mu}_t^{r,d}(x,y) = \hat{\mu}_t^{r,s}(x,y) = \hat{\mu}_t^r(x,y)$ and taking the product of the two expressions above yields the marriage matching function

$$\hat{\mu}_t^r(x,y) = \exp\left(\frac{\overline{V}_t^r(x,y) - w_t^r(x,y)}{2}\right)\sqrt{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)}.$$

The accounting constraints and law of motion describe how the counts must evolve over

time. The accounting constraints are given by

$$m_t(x) = \sum_{r \in \mathcal{R}} \sum_{y \in \mathcal{Y}} \mu_t^r(x, y) + \mu_t(x, 0) \text{ for all } x \in \mathcal{X}$$

and

$$f_t(y) = \sum_{r \in \mathcal{R}} \sum_{x \in \mathcal{X}} \mu_t^r(x, y) + \mu_t(0, y) \text{ for all } y \in \mathcal{Y}$$

where $\mu_t^r(x, y)$ is the total number of $(x, y; r)$ matches at the end of period t and $\mu_t(x, 0)$ and $\mu_t(0, y)$ are the analogous quantities of singles. This merely says that all men and women in the population must be either matched or single.

The laws of motion describe how the stocks of marriages and singles update over time as a function of outflows (marriage/cohabitation) and inflows (divorce/separation).[21] Let $\tilde{\mu}_t^r(x, y)$ be the number of $(x, y; r)$ matches at the start of time t, then the total number of such matches at the end of the period must be

$$\mu_t^r(x, y) = [1 - \delta_t^r(x, y)]\tilde{\mu}_t^r(x, y) + \hat{\mu}_t^r(x, y)$$

where $\delta_t^r(x, y)$ is the separation rate. Similarly, the number of singles at the end of the period must be given by

$$\mu_t(x, 0) = \tilde{\mu}_t(x, 0) - \sum_{r \in \mathcal{R}} \sum_{y \in \mathcal{Y}} \hat{\mu}_t^r(x, y) + \sum_{r \in \mathcal{R}} \sum_{y \in \mathcal{Y}} \delta_t^r(x, y)\tilde{\mu}_t^r(x, y)$$

and

$$\mu_t(0, y) = \tilde{\mu}_t(0, y) - \sum_{r \in \mathcal{R}} \sum_{x \in \mathcal{X}} \hat{\mu}_t^r(x, y) + \sum_{r \in \mathcal{R}} \sum_{x \in \mathcal{X}} \delta_t^r(x, y)\tilde{\mu}_t^r(x, y)$$

for men and women of type x and y, respectively.

□

A.2.1 Bargaining share

As mentioned in Proposition 4, the bargaining share $\theta_t^r(x, y)$ can be obtained from a step in the derivation of the matching function. I'll briefly describe how that works here and the additional assumption that needs to be made regarding the cost-sharing parameter $\eta_t^r(x, y)$.

[21] This is assuming that the underlying size of the population is stationary. However, it could be generalized to allow for exogenous increases in population. For example, if there is say a large influx of immigrants in a given period, this will act like an exogenous shock to the distribution of both matches and singles.

Consider the demand and supply equations in equilibrium given by

$$\hat{\mu}_t^r(x,y) = \hat{\mu}_t(x,0)\exp\left\{\theta_t^r(x,y)\overline{S}_t^r(x,y) - \eta_t^r(x,y)w_t^r(x,y)\right\}$$

and

$$\hat{\mu}_t^r(x,y) = \hat{\mu}_t(0,y)\exp\left\{\left[1-\theta_t^r(x,y)\right]\overline{S}_t^r(x,y) - \left[1-\eta_t^r(x,y)\right]w_t^r(x,y)\right\},$$

respectively. Taking the natural log of the ratio of these two expressions provides

$$\log\hat{\mu}_t(x,0) - \log\hat{\mu}(0,y) = \overline{V}_t^r(x,y)(1-2\theta_t^r(x,y)) - w_t^r(x,y)(1-2\eta_t^r(x,y)). \tag{a.6}$$

This defines a system of $T\times|\mathcal{R}|\times|\mathcal{X}|\times|\mathcal{Y}|$-many equations and $2\times T\times|\mathcal{R}|\times|\mathcal{X}|\times|\mathcal{Y}|$-many unknowns since both the θ's and η's need to be estimated. Thus in general, the parameters in system are unidentified and additional restrictions must be made. One approach would be to restrict the indicies over which these parameters vary, say, $\theta_t^r(x,y) = \theta(x,y)$ for all $t\in\{1,\cdots,T\}$ and $r\in\mathcal{R}$ and apply a similar restriction to η. However, instead I will simply follow Ciscato (2024) and assume that $\eta_t^r = \theta_t^r(x,y)$ for all $t\in\{1,\cdots,T\}$, $r\in\mathcal{R}$, $x\in\mathcal{X}$, and $y\in\mathcal{Y}$. In this formulation, they split the formation cost according to their bargaining share, which is determined by their relative scarcity on the market. Under this assumption, rearranging Equation a.6 yields Equation 15.

A.3 Extending the model to include fertility

The natural way to add fertility to the model is to augment the notion of an arrangement r. Now let $r_k\in\mathcal{R} = \{C_k, M_k\}_{k\in\mathbb{Z}_+}$ be a co-residential arrangement, of type either C or M, with k-many couple-specific children. It is also possible that couples can begin a co-residential relationship with $k>0$. This is done because there is a non-negligible number of matches in the data for which this is true. That is, either a couple has a child before they become cohabiting or marry, or alternatively, in the same period they both enter a co-residential arrangement and also have a child. Most estimators presented in Section 3 work identically if one allows for the possibility of children. The largest difference comes down to how arrangement transitions are specified and how the separation cost is estimated as it now needs to depend on the number of children a couple has.

For couples who are currently matched, consider individuals i and j of types x and y who are matched in time t in arrangement r_k. At the start of the period, they face a joint preference shock r_k over the types of feasible arrangements. I'll denote the set of feasible arrangements $\mathcal{R}_k\in\{\mathcal{M}_k,\mathcal{C}_k\}$ which depends on both their current arrangement r and the

number of kids they have k. For example, if married, they can choose to either remain married with their current number of children k or increase k by one. Thus, their choice set is $\mathcal{M}_k = \{M_k, M_{k+1}\}$. Cohabiting couples also have the choice of transition to marriage so their choice set is $\mathcal{C}_k = \{C_k, C_{k+1}, M_k, M_{k+1}\}$. At the start of the period, the preference shock over possible arrangements is revealed, the couple will then consider the expected value of each possible arrangement and the transition cost to choose an optimal arrangement r^*. That is, they face the discrete choice problem

$$r^* = \underset{r \in \mathcal{R}_k}{\operatorname{argmax}} \{\overline{V}_t^r(x,y) - w_t^{r|r_k}(x,y) + \varepsilon_{ijt}^r(x,y)\}. \tag{a.7}$$

After they choose r^*, the match-quality shock $w_{ijt}^{r^*}$ is revealed and they bargain over the utility generated by the match. This value of the match is the same as that which is given in Equation 7. Assume that that elements of the set of preference shocks $\boldsymbol{\varepsilon}_{ijt}^{r_k} = [\varepsilon_{ijt}^{\tilde{r}}]_{\tilde{r} \in \mathcal{R}_k}$ are independent from the elements of set of match-quality shocks $\boldsymbol{\omega}_{ijt}^{r_k} = [\omega_{ijt}^{\tilde{r}}]_{\tilde{r} \in \mathcal{R}_k}$. Furthermore, assume the elements of $\boldsymbol{\varepsilon}_{ijt}^{r_k}$ and $\boldsymbol{\omega}_{ijt}^{r_k}$ are i.i.d. GEV I distributed. Under these conditions, there exists closed-form expressions for three different probabilities that will be needed to solve the model.

The probability that a couple transitions from arrangement r_k to arrangement r^* is given by

$$\mathbb{P}_t(r^*|x,y,r_k) = \frac{\exp\left\{\overline{V}_t^{r^*}(x,y) - w_t^{r^*|r_k}(x,y)\right\}}{\sum_{r \in \mathcal{R}_k} \exp\left\{\overline{V}_t^{r}(x,y) - w_t^{r|r_k}(x,y)\right\}}.$$

Let $d_{ijt}^{r*}(x,y) \in \{0,1\}$ be an indicator which is equal to one if individuals i and j who have transitioned to an $(x,y;r^*)$ match in time t dissolve their relationship, and zero otherwise. The probability that this event occurs is given by

$$\mathbb{P}_t\left(d_{ijt}^{r^*}(x,y) = 1\right) = \left(1 + \exp\{\pi_t^{r^*}(x,y) + \kappa_t^{r^*}(x,y)\}\right)^{-1}. \tag{a.8}$$

Finally, given that the preference shocks $\boldsymbol{\varepsilon}_{ijt}^{r_k}$ and match-quality shocks $\boldsymbol{\omega}_{ijt}^{r_k}$ are assumed to be independent of one another, the probability that an $(x,y;r_k)$ match successfully transitions to a new arrangement r^* can be written as

$$\mathbb{P}_t(r^*|x,y,r_k)\mathbb{P}_t(d_{ijt}^{r^*}(x,y) = 0) = \frac{\exp\left\{\overline{V}_t^{r^*}(x,y) - w_t^{r^*|r_k}(x,y)\right\}}{\sum_{r \in \mathcal{R}_k} \exp\left\{\overline{V}_t^{r}(x,y) - w_t^{r|r_k}(x,y)\right\}} \left(1 + \exp\{\pi_t^{r^*}(x,y) + \kappa_t^{r^*}(x,y)\}\right)^{-1}.$$

Once agents can make fertility decisions, this changes the separation cost. I will state this

as a proposition.

Proposition 7. *Under the expanded arrangement space* $\mathcal{R} = \{C_k, M_k\}_{k\in\mathbb{Z}_+}$*, the separation cost is given by*

$$\kappa_t^{r_k}(x,y) = \sum_{s=0}^{k} \left(\Lambda_t^{r_s}(x,y) - \hat{\Lambda}_t^{r_s}(x,y)\right). \tag{a.9}$$

Proof. First note the following property of the natural logarithm. If $0 \leq a \leq 1$ and $0 \leq b \leq 1$ then one may write

$$\log\left(\frac{1-a}{a}\right) - \log\left(\frac{1-b}{b}\right) = \log\left(\frac{(1-a)b}{(1-b)a}\right).$$

From the proof of Proposition 6 I have that

$$\pi_t^{r_0}(x,y) = \log\left(\frac{1-\hat{\hat{\delta}}_t^{r_0}(x,y)}{\hat{\hat{\delta}}_t^{r_0}(x,y)}\right).$$

There exists a similar expression which relates $\pi_t^{r_0}(x,y)+\kappa_t^{r_0}(x,y)$ to the observed separation rate

$$\pi_t^{r_0}(x,y) + \kappa_t^{r_0}(x,y) = \log\left(\frac{1-\hat{\delta}_t^{r_0}(x,y)}{\hat{\delta}_t^{r_0}(x,y)}\right). \tag{a.10}$$

Therefore, these two can be combined to provide

$$\kappa_t^{r_0}(x,y) = \log\left(\frac{1-\hat{\delta}_t^{r_0}(x,y)}{\hat{\delta}_t^{r_0}(x,y)}\right) - \log\left(\frac{1-\hat{\hat{\delta}}_t^{r_0}(x,y)}{\hat{\hat{\delta}}_t^{r_0}(x,y)}\right).$$

Using the above logarithm identity provides

$$\kappa_t^{r_0}(x,y) = \log\left[\frac{\left(1-\hat{\delta}_t^{r_0}(x,y)\right)\hat{\hat{\delta}}_t^{r_0}(x,y)}{\left(1-\hat{\hat{\delta}}_t^{r_0}(x,y)\right)\hat{\delta}_t^{r_0}(x,y)}\right].$$

Now consider the case when $k > 0$ which we can do iteratively. From Equation **??** it is known that

$$\pi_t^{r_1}(x,y) + \kappa_t^{r_0}(x,y) = \log\left(\frac{1-\hat{\hat{\delta}}_t^{r_1}(x,y)}{\hat{\hat{\delta}}_t^{r_1}(x,y)}\right)$$

and since $\kappa_t^{r_0}(x,y)$ is known we can write

$$\pi_t^{r_1}(x,y) = \log\left(\frac{1-\hat{\tilde{\delta}}_t^{r_1}(x,y)}{\hat{\tilde{\delta}}_t^{r_1}(x,y)}\right) - \log\left[\frac{\left(1-\hat{\delta}_t^{r_0}(x,y)\right)\hat{\tilde{\delta}}_t^{r_0}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_0}(x,y)\right)\hat{\delta}_t^{r_0}(x,y)}\right]$$

Using Equation a.10 again implies that I can write

$$\begin{aligned}
\kappa_t^{r_1}(x,y) &= \log\left(\frac{1-\hat{\delta}_t^{r_1}(x,y)}{\hat{\delta}_t^{r_1}(x,y)}\right) - \log\left(\frac{1-\hat{\tilde{\delta}}_t^{r_1}(x,y)}{\hat{\tilde{\delta}}_t^{r_1}(x,y)}\right) + \kappa_t^{r_0}(x,y) \\
&= \log\left[\frac{\left(1-\hat{\delta}_t^{r_1}(x,y)\right)\hat{\tilde{\delta}}_t^{r_1}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_1}(x,y)\right)\hat{\delta}_t^{r_1}(x,y)}\right] + \log\left[\frac{\left(1-\hat{\delta}_t^{r_0}(x,y)\right)\hat{\tilde{\delta}}_t^{r_0}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_0}(x,y)\right)\hat{\delta}_t^{r_0}(x,y)}\right] \\
&= \log\left[\frac{\left(1-\hat{\delta}_t^{r_1}(x,y)\right)\hat{\tilde{\delta}}_t^{r_1}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_1}(x,y)\right)\hat{\delta}_t^{r_1}(x,y)}\frac{\left(1-\hat{\delta}_t^{r_0}(x,y)\right)\hat{\tilde{\delta}}_t^{r_0}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_0}(x,y)\right)\hat{\delta}_t^{r_0}(x,y)}\right].
\end{aligned}$$

Performing an identical procedure for the case where $k=2$ this gives

$$\begin{aligned}
\kappa_t^{r_2}(x,y) &= \log\left(\frac{1-\hat{\delta}_t^{r_2}(x,y)}{\hat{\delta}_t^{r_2}(x,y)}\right) - \log\left(\frac{1-\hat{\tilde{\delta}}_t^{r_2}(x,y)}{\hat{\tilde{\delta}}_t^{r_2}(x,y)}\right) + \kappa_t^{r_1}(x,y) \\
&= \log\left[\frac{\left(1-\hat{\delta}_t^{r_2}(x,y)\right)\hat{\tilde{\delta}}_t^{r_2}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_2}(x,y)\right)\hat{\delta}_t^{r_2}(x,y)}\right] + \log\left[\frac{\left(1-\hat{\delta}_t^{r_1}(x,y)\right)\hat{\tilde{\delta}}_t^{r_1}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_1}(x,y)\right)\hat{\delta}_t^{r_1}(x,y)}\frac{\left(1-\hat{\delta}_t^{r_0}(x,y)\right)\hat{\tilde{\delta}}_t^{r_0}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_0}(x,y)\right)\hat{\delta}_t^{r_0}(x,y)}\right] \\
&= \log\left[\frac{\left(1-\hat{\delta}_t^{r_2}(x,y)\right)\hat{\tilde{\delta}}_t^{r_2}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_2}(x,y)\right)\hat{\delta}_t^{r_2}(x,y)}\frac{\left(1-\hat{\delta}_t^{r_1}(x,y)\right)\hat{\tilde{\delta}}_t^{r_1}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_1}(x,y)\right)\hat{\delta}_t^{r_1}(x,y)}\frac{\left(1-\hat{\delta}_t^{r_0}(x,y)\right)\hat{\tilde{\delta}}_t^{r_0}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_0}(x,y)\right)\hat{\delta}_t^{r_0}(x,y)}\right]
\end{aligned}$$

and then by iterating this gives

$$\kappa_t^{r}(x,y) = \log\left[\prod_{s=0}^{k}\frac{\left(1-\hat{\delta}_t^{r_s}(x,y)\right)\hat{\tilde{\delta}}_t^{r_s}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_s}(x,y)\right)\hat{\delta}_t^{r_s}(x,y)}\right]. \tag{a.11}$$

To simplify this, note that the term inside the product can be rewritten as

$$\frac{\left(1-\hat{\delta}_t^{r_s}(x,y)\right)\hat{\tilde{\delta}}_t^{r_s}(x,y)}{\left(1-\hat{\tilde{\delta}}_t^{r_s}(x,y)\right)\hat{\delta}_t^{r_s}(x,y)} = e^{\Lambda_t^{r_s}(x,y)-\hat{\Lambda}_t^{r_s}(x,y)}$$

where $\Lambda_t^{r^s}(x,y)$ and $\hat{\Lambda}_t^{r^s}(x,y)$ are defined by Equations 17 and 23, respectively. Thus, Equation a.11 reduces to

$$\kappa_t^r(x,y) = \sum_{s=0}^{k} \left(\Lambda_t^{r^s}(x,y) - \hat{\Lambda}_t^{r^s}(x,y) \right)$$

as claimed. □

A.4 Proof of Lemma 1

First let's explore the limit of the bargaining share as the number of male singles tends to infinity. One can rewrite the bargaining share as

$$\theta_t^r(x,y) = \frac{\log\left(\frac{\hat{\mu}_t^r(x,y)}{\hat{\mu}_t(x,0)}\right)}{\log\left(\frac{\hat{\mu}_t^r(x,y)^2}{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)}\right)}$$

thus in

$$\lim_{\hat{\mu}_t(x,0)\to\infty} \frac{\log\left(\frac{\hat{\mu}_t^r(x,y)}{\hat{\mu}_t(x,0)}\right)}{\log\left(\frac{\hat{\mu}_t^r(x,y)^2}{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)}\right)}$$

both the numerator and denominator are tending to zero. However, since these both simply behave like $\log \hat{\mu}_t(x,0)$ as $\hat{\mu}_t(x,0) \to \infty$, this ratio is tending to 1 implying that

$$\lim_{\hat{\mu}_t(x,0)\to\infty} \theta_t^r(x,y) = 1.$$

To compute the limit as $\hat{\mu}_t^r(x,y) \to \infty$, leave the expression as it is written in Lemma 1 and factor $\hat{\mu}_t^r(x,y)$ from both the numerator and the denominator. This provides,

$$\theta_t^r(x,y) = \frac{\log \hat{\mu}_t^r(x,y) - \log \hat{\mu}_t(x,0)}{2\log \hat{\mu}_t^r(x,y) - \log \hat{\mu}_t(x,0) - \log \hat{\mu}_t(0,y)} = \frac{\log \hat{\mu}_t^r(x,y)\left(1 - \frac{\log \hat{\mu}_t(x,0)}{\log \hat{\mu}_t^r(x,y)}\right)}{\log \hat{\mu}_t^r(x,y)\left(2 - \frac{\log \hat{\mu}_t(x,0)}{\log \hat{\mu}_t^r(x,y)} - \frac{\log \hat{\mu}_t(0,y)}{\log \hat{\mu}_t^r(x,y)}\right)}.$$

One may cancel $\log \hat{\mu}_t^r(x,y)$ from the top and bottom and then take the limit to get

$$\lim_{\hat{\mu}_t^r(x,y)\to\infty} \theta_t^r(x,y) = \lim_{\hat{\mu}_t^r(x,y)\to\infty} \frac{\left(1 - \frac{\log \hat{\mu}_t(x,0)}{\log \hat{\mu}_t^r(x,y)}\right)}{\left(2 - \frac{\log \hat{\mu}_t(x,0)}{\log \hat{\mu}_t^r(x,y)} - \frac{\log \hat{\mu}_t(0,y)}{\log \hat{\mu}_t^r(x,y)}\right)} = \frac{1-0}{2-0-0} = \frac{1}{2}$$

as claimed. For the next part, differentiate $\theta_t^r(x,y)$ with respect to $\hat{\mu}_t(x,0)$. Using the quotient rule this gives

$$\begin{aligned}
\frac{\partial \theta_t^r(x,y)}{\partial \hat{\mu}_t(x,0)} &= \frac{\left[\frac{\partial}{\partial \hat{\mu}_t(x,0)} \log\left(\frac{\hat{\mu}_t^r(x,y)}{\hat{\mu}_t(x,0)}\right)\right] \log\left(\frac{\hat{\mu}_t^r(x,y)^2}{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)}\right) - \log\left(\frac{\hat{\mu}_t^r(x,y)}{\hat{\mu}_t(x,0)}\right)\left[\frac{\partial}{\partial \hat{\mu}_t(x,0)} \log\left(\frac{\hat{\mu}_t^r(x,y)^2}{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)}\right)\right]}{\left[\log\left(\frac{\hat{\mu}_t^r(x,y)^2}{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)}\right)\right]^2}. \\
&= \frac{-\frac{1}{\hat{\mu}_t(x,0)} \log\left(\frac{\hat{\mu}_t^r(x,y)^2}{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)}\right) - \log\left(\frac{\hat{\mu}_t^r(x,y)}{\hat{\mu}_t(x,0)}\right)\left(-\frac{1}{\hat{\mu}_t(x,0)}\right)}{\left[\log\left(\frac{\hat{\mu}_t^r(x,y)^2}{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)}\right)\right]^2} \\
&= \frac{\frac{1}{\hat{\mu}_t(x,0)}\left[-(2\log\hat{\mu}_t^r(x,y) - \log\hat{\mu}_t(x,0) - \log\hat{\mu}_t(0,y)) + (\log\hat{\mu}_t^r(x,y) - \log\hat{\mu}_t(0,y))\right]}{\left[\log\left(\frac{\hat{\mu}_t^r(x,y)^2}{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)}\right)\right]^2} \\
&= \frac{\frac{1}{\hat{\mu}_t(x,0)}\left[\log\hat{\mu}_t(0,y) - \log\hat{\mu}_t^r(x,y)\right]}{\left[\log\left(\frac{\hat{\mu}_t^r(x,y)^2}{\hat{\mu}_t(x,0)\hat{\mu}_t(0,y)}\right)\right]^2}.
\end{aligned}$$

Since the denominator is always positive, this establishes the result that

$$\begin{aligned}
\frac{\partial \theta_t^r(x,y)}{\partial \hat{\mu}_t(x,0)} &> 0 \text{ if } \hat{\mu}_t(0,y) > \hat{\mu}_t^r(x,y) \\
\frac{\partial \theta_t^r(x,y)}{\partial \hat{\mu}_t(x,0)} &< 0 \text{ if } \hat{\mu}_t(0,y) < \hat{\mu}_t^r(x,y) \\
\frac{\partial \theta_t^r(x,y)}{\partial \hat{\mu}_t(x,0)} &= 0 \text{ if } \hat{\mu}_t(0,y) = \hat{\mu}_t^r(x,y).
\end{aligned}$$

□

A.5 Simulating counterfactual outcomes

Here I will describe how to use the model to generate counterfactual matching equilibria. It should be noted that this is not all that can be done with the model as here I will not be explicitly considering the systematic surplus and match-dissolution costs in the simulation procedure. However, this could easily be added if it was of interest to the researcher. To outline the process, first let

$$\Phi_t^r(x,y) = \exp\left(\frac{\overline{V}_t^r(x,y) - w_t^r(x,y)}{2}\right)$$

represent the net gain to matching. From the matching function I can construct a system of $|\mathcal{R}| \times |\mathcal{X}| \times |\mathcal{Y}|$ equations in each period t of the form

$$\hat{\mu}_t^r(x,y) = \exp\left(\frac{\overline{V}_t^r(x,y) - w_t^r(x,y)}{2}\right)\sqrt{\left(\tilde{\mu}_t(x,0) - \sum_{y\in\mathcal{Y}}\sum_{r\in\mathcal{R}}\hat{\mu}_t^r(x,y)\right)\left(\tilde{\mu}_t(0,y) - \sum_{x\in\mathcal{X}}\sum_{r\in\mathcal{R}}\hat{\mu}_t^r(x,y)\right)}. \tag{a.12}$$

$\tilde{\mu}_t(x,0)$ and $\tilde{\mu}_t(0,y)$ are the numbers of singles at the start of period t. Similarly, let $\tilde{\mu}_t^r(x,y)$ be the starting stock of $(x,y;r)$ couples in period t. The number of singles at the beginning of a period arise endogenously in the model through laws of motion

$$\tilde{\mu}_t(x,0) = \tilde{\mu}_{t-1}(x,0) - \sum_{y\in\mathcal{Y}}\sum_{r\in\mathcal{R}}\hat{\mu}_{t-1}^r(x,y) + \sum_{y\in\mathcal{Y}}\sum_{r\in\mathcal{R}}\tilde{\delta}_{t-1}^r(x,y)\tilde{\mu}_{t-1}^r(x,y)$$

and

$$\tilde{\mu}_t(0,y) = \tilde{\mu}_{t-1}(0,y) - \sum_{x\in\mathcal{X}}\sum_{r\in\mathcal{R}}\hat{\mu}_{t-1}^r(x,y) + \sum_{x\in\mathcal{X}}\sum_{r\in\mathcal{R}}\tilde{\delta}_{t-1}^r(x,y)\tilde{\mu}_{t-1}^r(x,y).$$

The separation rate $\tilde{\delta}_{t-1}^r(x,y)$ comes from the estimate of $\overline{V}_t^r(x,y)$. Under the logit assumption, this is simply

$$\tilde{\delta}_{t-1}^r(x,y) = \frac{1}{1+\exp(\overline{V}_t^r(x,y))}.$$

There are also laws of motion for the number of starting matches $\tilde{\mu}_t^r(x,y)$ which depend on arrangement r. For marriage, this is given by

$$\tilde{\mu}_t^M(x,y) = \tilde{\mu}_{t-1}^M(x,y) + \hat{\mu}_t^M(x,y) - \tilde{\delta}_{t-1}^M(x,y)\tilde{\mu}_{t-1}^M(x,y) + \hat{\mu}_{t-1}^{M|C}(x,y)$$

which takes into account new matches, divorces, and also the couples who transition from cohabitation to marriage. The analogous expression for cohabitation is given by

$$\tilde{\mu}_t^C(x,y) = \tilde{\mu}_{t-1}^C(x,y) + \hat{\mu}_t^C(x,y) - \tilde{\delta}_{t-1}^C(x,y)\tilde{\mu}_{t-1}^C(x,y) - \hat{\mu}_{t-1}^{M|C}(x,y).$$

Finally, $\hat{\mu}_{t-1}^{M|C}(x,y)$ also arises endogenously as,

$$\hat{\mu}_t^{M|C}(x,y) = \mathbb{P}_t(M|x,y,C)\tilde{\mu}_t^C(x,y) = \frac{\exp\left\{\overline{V}_t^M(x,y) - w_t^{M|C}(x,y)\right\}}{\exp\left\{\overline{V}_t^M(x,y) - w_t^{M|C}(x,y)\right\} + \exp\left\{\overline{V}_t^C(x,y)\right\}} \times \tilde{\mu}_t^C(x,y).$$

Consider two sets of model estimates A and CF to denote "actual" and "counterfactual". The procedure can be summarized as,

1. Generate actual and counterfactual estimates of relevant quantities

$$\{\overline{V}_t^{r,(A)}(x,y), w_t^{r,(A)}(x,y), w_t^{M|C,(A)}(x,y)\}_{x\in\mathcal{X},y\in\mathcal{Y},r\in\mathcal{R}}$$

and

$$\{\overline{V}_t^{r,(CF)}(x,y), w_t^{r,(CF)}(x,y), w_t^{M|C,(CF)}(x,y)\}_{x\in\mathcal{X},y\in\mathcal{Y},r\in\mathcal{R}}$$

for periods $t = 1, \cdots, T$.

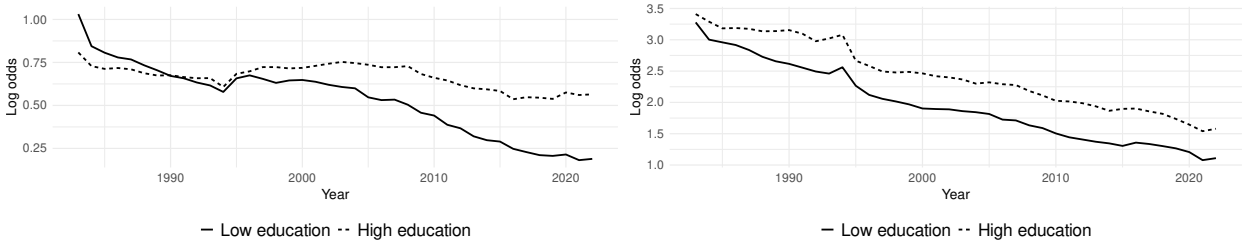
2. Collect the number of starting singles $\{\tilde{\mu}_t(x,0), \tilde{\mu}_t(0,y)\}$ and starting couples $\tilde{\mu}_t^r(x,y)$ for $(x,y;r) \in \mathcal{R}\times\mathcal{X}\times\mathcal{Y}$.

   For both A and CF:

3. Solve the system of equations given in a.12.
4. Compute the separation rate $\tilde{\delta}_t^r(x,y)$ and transition probability $\mathbb{P}_t(M|x,y,C)$.
5. Update stock of singles $\{\tilde{\mu}_{t+1}(x,0), \tilde{\mu}_{t+1}(0,y)\}$ and starting couples $\tilde{\mu}_{t+1}^r(x,y)$ using the laws of motion.
6. Repeat until period T.

B Additional tables & figures

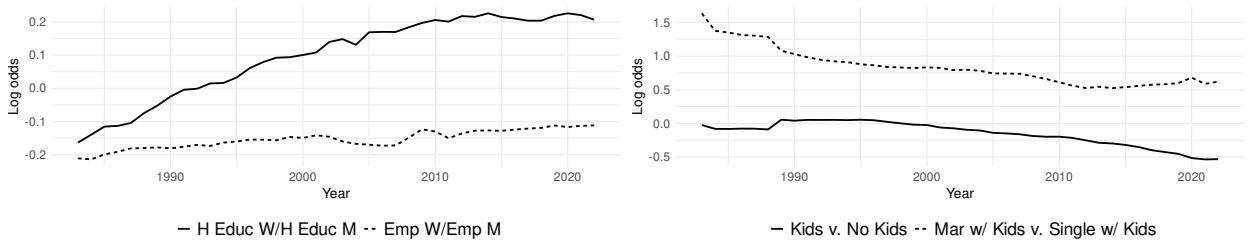
B.1 More features of the second demographic transition



(a) Matched v. single by education level (b) Married v. cohabiting by education level

Figure B.1: Trends in matching patterns by education level

Figure B.2 shows additional features of the SDT. In B.1a, the plot shows the log odds of number of married individuals to the number of individuals who are single in year t. It is clear that those with low educational attainment levels have gradually over time become less likely



(a) Education and employment

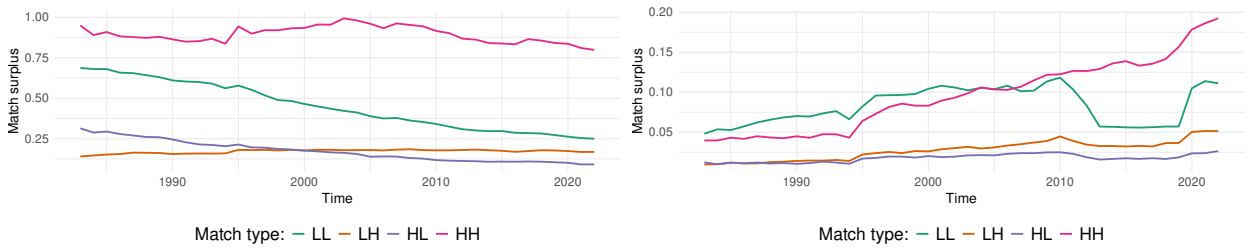
(b) Fertility

Figure B.2: Other trends from the second demographic transition

to be matched—either married or cohabiting—while this trend has only appeared recently for the high-education group. In contrast, for both high and low education groups, cohabitation is becoming a more popular form of coresidential arrangement as shown in Figure B.1b. While not the focus of this analysis, Figure B.2a shows another salient characteristic of the SDT. That is, women becoming relatively more educated than men on average and increased female share of the labour force. Women became more likely to have a college education or greater beginning in the early 1990s and this ratio continued to increase until only very recently where it has levelled off. Additionally, as shown by the dotted line in Figure B.2a, women's share of the labour force has also been steadily increasing over the last 40 years. However, men are still more likely to be employed than women. Figure B.2b shows two interesting patterns regarding changes in fertility choices since 1983. The dotted line suggests that the prevalence of married parents was decreasing until relatively recently but has rebounded slightly in the last decade. At the same time, it can be seen that the share of individuals who have children has declined as evidenced by the solid black line. One possible explanation for these patterns is the dramatic reduction in instances of teenage pregnancy in the US. According the Office of Population Affairs, in 2022 the teen birth rate was 13.6 per 1000 females ages 15–19 compared to the peak rate in 1991 of 61.8 births per female ages 15–19.

B.2 Estimates using static model

These figures are generated by using cross-sectional stocks of who is matched with whom and the number of singles in each year t using Equation **??**. These are to be contrasted with the estimates using flows given in Section 5.1. We can see that the trend for marriages is not entirely dissimilar whereby the LL types see less return to matching over time and the heterogamous types have persistently low returns to matching. Similarly, there is no discernible trend in surplus or expected return to matching for the HH types—it is consistently high. Again, this is something well known in the literature. There is a bit of difference compar-



(a) Marriage

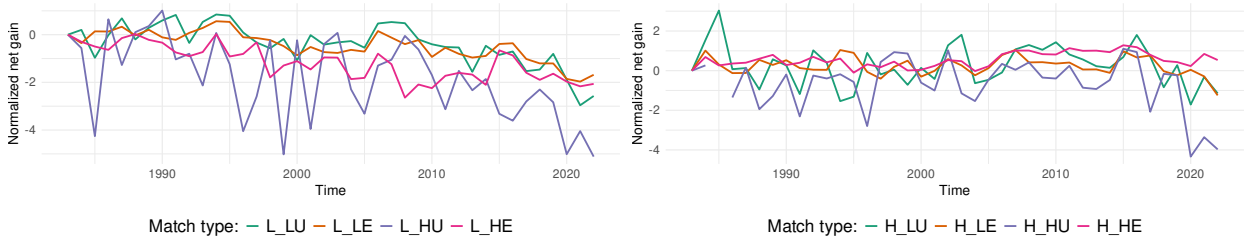
(b) Cohabitation

Figure B.3: Match surplus estimates by education types

ing the cohabitation estimates between the static and dynamic case. In the stati case, the HH-type matches see persistent increases in the gains to matching. This is true too in the dynamic model but this trend begins to reverse starting after 2008. Also, the LL types see a decline in expected returns to matching starting around similar times in both the static and the dynamic estimates.

What this suggests is that largely these two methods agree when assessing the total return to matching for different types of couples. However, the advantage of the dynamic approach using flows instead of stocks is that one may separate the expected returns into two components: expected match value and match-formation cost. This is what I do in Section 5.1.

B.3 Education-employment types



(a) Difference between cost and match value—low-education women

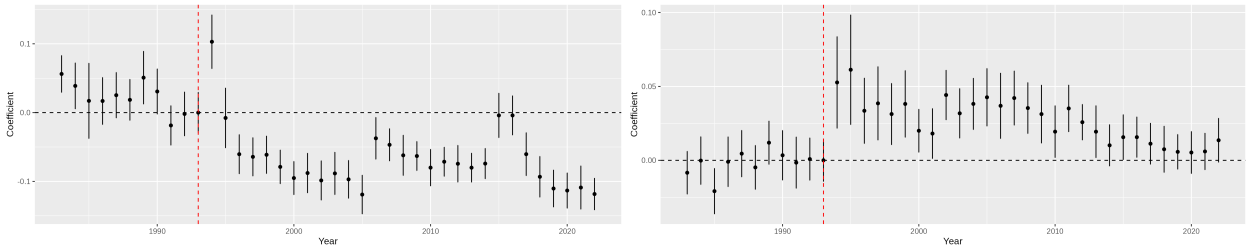
(b) Difference between cost and match value—high-education women

Figure B.4: Comparing cost and match value for marriage: education/employment groups

As an addition to the discussion in Section 5.2, an interesting idea is to ask if we can infer any differences in matching outcomes if we split men into education-employment categories. This can provide additional context for the marriageable men hypothesis as discussed by Chambers et al. (2025). I show the result of this in Figure B.4 and it tells an interesting story. Here the type labels can be read as H_LE to mean a high-education woman matched

with a low-education man who is employed. If the second character in the man's type is U, this implies they are unemployed. In particular, it can be seen that the high-educated women continue to match with all types of men, employed or unemployed, at the same rate as before. Whereas for low education women, matches of all types are less common today than 40 years ago. While employment status is not a perfect proxy for marriageability, it provides some insight that the men and women have different experiences on the matching market even when holding education levels fixed. It isn't necessarily the case that high-education women are "skimming" the marriageable men of low-education status off the market. Instead, it appears that these women are crowding out the low education women from all types of matches. Of course, there is much more that could be said about this and it is left for future research.

B.4 Other measurements of cohabitation



(a) One-year hazard: POSSLQ to marriage (b) One-year hazard: fertility for POSSLQs

Figure B.5: Recreating Figure (12) using an alternative measure of cohabitation

To ensure that the changes observed are not simply coming from the cohabitation prediction procedure, I display alternative versions of the figures shown in Section (5.2) using POSSLQ instead of the indicator generated by the neural network described in Section (C.1). Whether a household contains persons of the same sex sharing living quarters, it must meet a set of criteria. The measure is use is the adjusted version suggested by Casper and Cohen (2000).

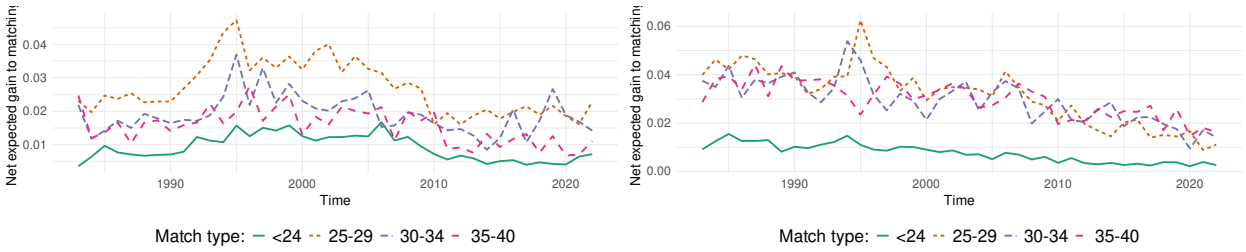
Definition B.1. *(Adjusted POSSLQ) A household is said to contain persons of opposite sex sharing living quarters if*

1. *The householder is at least 15 years of age.*
2. *The household contains one other person aged 15+ who is unrelated, not a foster child, and of the opposite sex as the householder.*
3. *The household does not contain any other persons aged 15+ aside from family members of the householder.*

It is clear from Figure B.5 that the pattern is largely identical regardless of which measurement is used to infer historical cohabitation. It should also be noted that no major changes to any of the relevant variables used to measure POSSLQ occurred around this time.

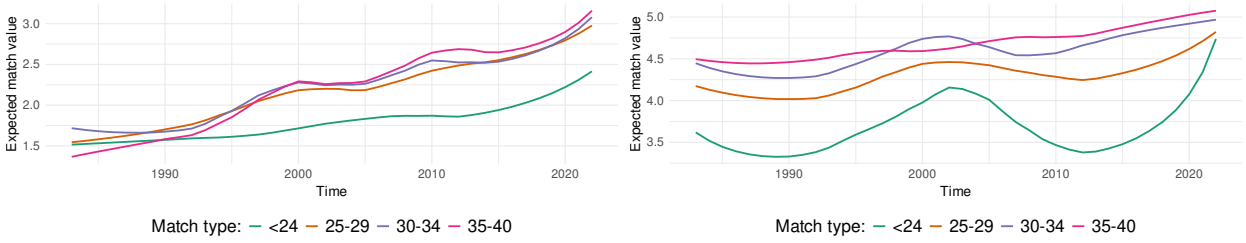
B.5 Structural parameter estimates using age types

The estimates presented in Figures B.7, B.8, B.9, B.10, and B.11 are the same parameters as those presented in Section 5.1 except using age types instead of education types.



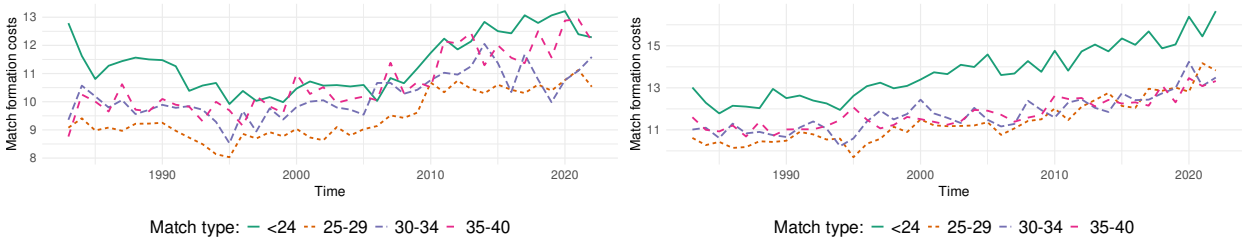
(a) Cohabitation (b) Marriage

Figure B.6: Net return to matching $\Phi_t^r(x, y)$



(a) Cohabitation (b) Marriage

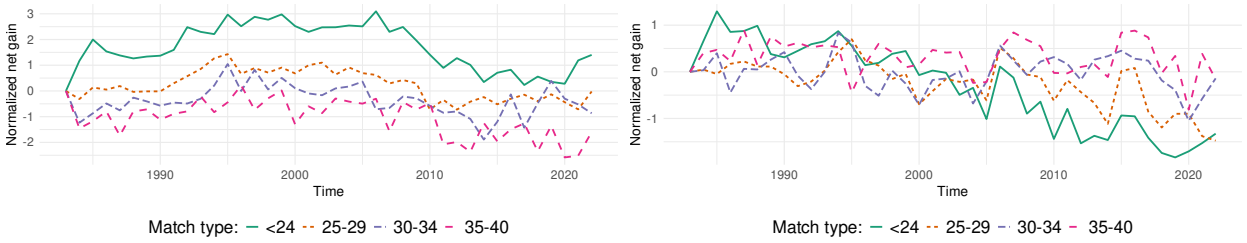
Figure B.7: Expected match value $\overline{V}_t^r(x, y)$



(a) Cohabitation (b) Marriage

Figure B.8: Match-formation costs $w_t^r(x, y)$

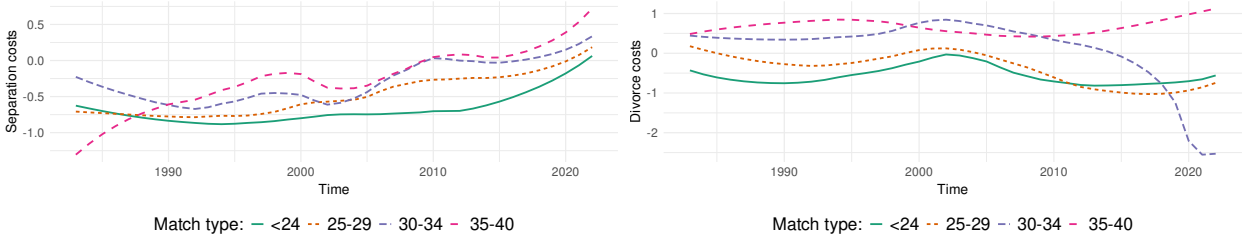
The net of the match-formation parameters shown in Figure B.6 reflect the fact that the youngest age group always has had the lowest return to matching. In the case of cohabitation,



(a) Cohabitation (b) Marriage

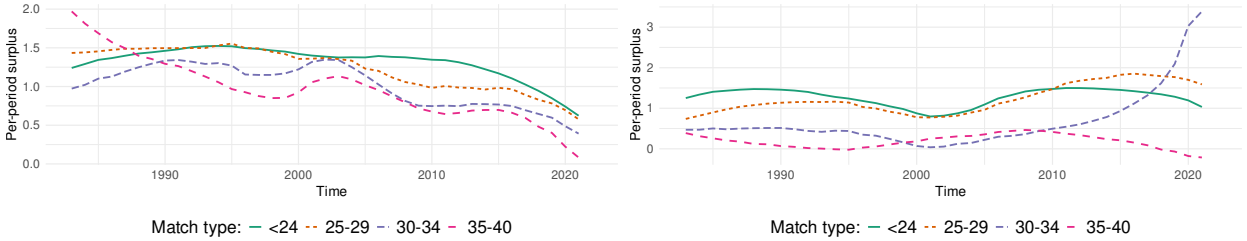
Figure B.9: Net returns adjusted such that $\Phi^r_{1983}(x, y) = 0$

this rose slightly during the 90s and up to 2008 where it then began to recede. In the case of marriage, it was always low and has been trending down for the last 40 years. Given that expected match value is largely increasing for both marriage and cohabitation during this period, as was the case with the education-type couples, the decreases in net returns come from increases in match-formation cost. Interestingly, the decline in net return for marriage is driven almost entirely by the youngest age group suggesting more of a delay phenomenon than an outright forgoing of marriage. This becomes particularly salient when looking at Figure B.9 which show that the declines in returns to marriage since 1983 concentrated in those aged 29 and under.



(a) Cohabitation (b) Marriage

Figure B.10: Match dissolution costs $\kappa^r_t(x, y)$



(a) Cohabitation (b) Marriage

Figure B.11: Systematic surplus $\pi^r_t(x, y)$

When looking at match stability parameters, it also largely tells the same story as that of the education types. For cohabitation, increased match stability comes from a combination of increasing dissolution costs and decreasing systematic surplus. For marriage, these have largely remained unchanged but there is a slight uptick in systematic surplus and a mild decline in dissolution costs. When comparing the scale of these estimates, it appears that the cohabitation surplus started very high and is trending down towards the level of marriage and while at the same time dissolution costs started low and have began to rise. This looks like a convergence of these two forms of coresidential arrangement whereby cohabitation and marriage are beginning to look more similar from a behavioural perspective.

C Additional notes on the data

C.1 Neural network approach to measuring historical cohabitation

The model takes household, demographic, and labour force characteristics as inputs and predicts a couple's cohabitation status. I also perform a logistic regression using the same set of explanatory variables as a benchmark. As a means of comparison, I've plotted the a few different estimates of the cohabitation rate in the population from the period 1977–2023 in Figure C.12.[22] Comparing the three CPS measurements POSSLQ, UP, and PECOHAB, given in red in Figure C.12, we can see from the points where we transition from one measurement to another that there is substantial variation in the number of estimated cohabitors depending on the measurement used. The neural network approach—given by the dotted blue line—provides a smoother transition across these three regimes and seems to partially address the known undercounting problem present in both POSSLQ and UP. It should be noted that, as one may expect given the discussion above, the predicted cohabitation rate is a little lower than the official CPS rate as measured by PECOHAB.

[22]The year 1976 is excluded for data quality issues discussed in Flood et al. (2022). Also note this is *very* preliminary—I am currently refining this prediction.

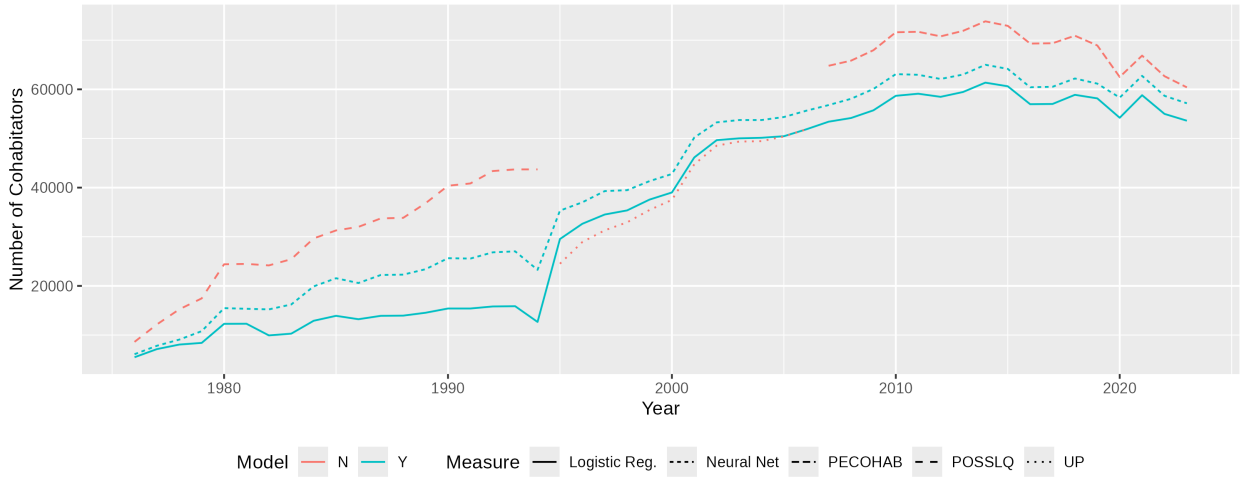


Figure C.12: Comparison of different measures of cohabitation in CPS

C.2 Divorce rate comparison

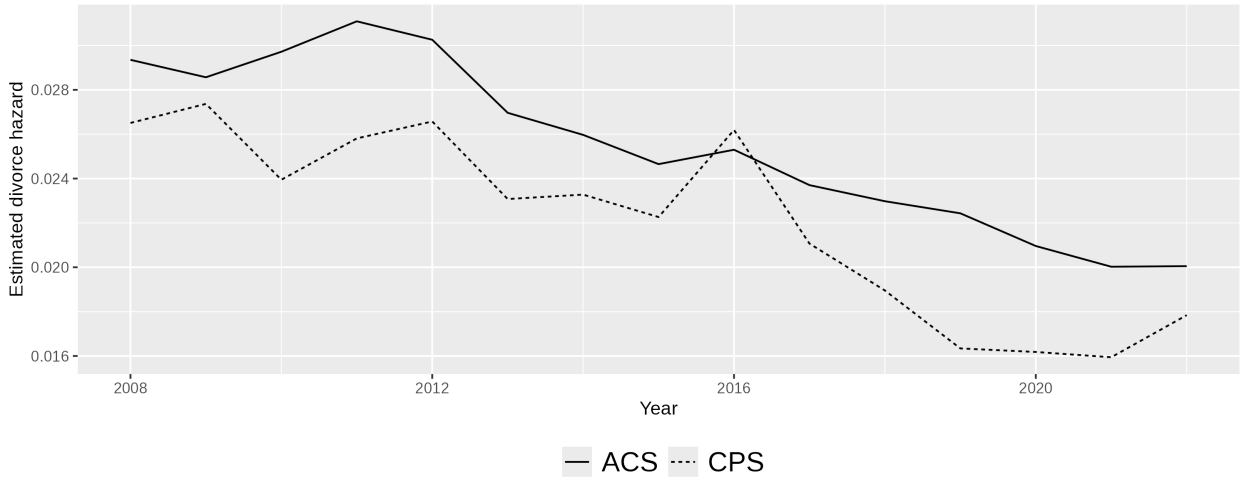


Figure C.13: Comparison of one-year divorce hazard

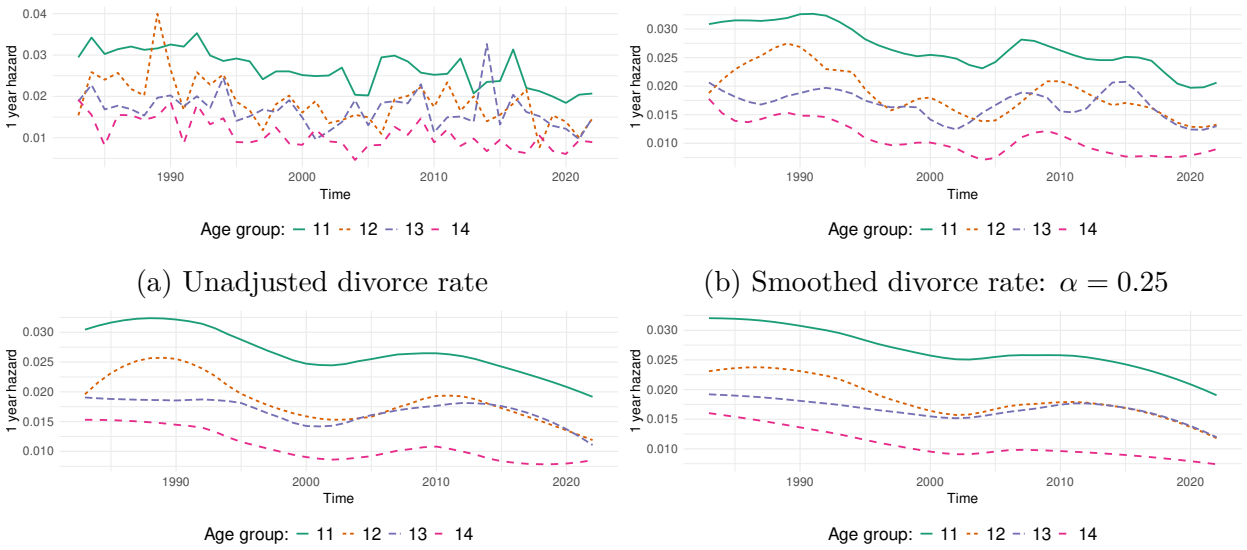
I mentioned in Section 4.3 that I am unable to track households who drop out between period t and t'. To assess the impact this has on the different data flows I'm tracking, I compare my estimates to a measurement that does not have this problem. In Figure C.13 I show the difference between two estimated the one-year divorce hazard rates. The solid line is calculated from the American Community Survey (ACS) and the dotted line are the estimates I calculate using the methodology outlined in Section 4.3. The reason to use the ACS as a benchmark is that it explicitly asks respondents whether they were divorced in the last 12 months. That is, there is no need to link individuals across samples to determine if they experienced a divorce. As such, one may expect that this is a more accurate estimate

of the divorce rate in the population. It seems that the CPS estimates are slightly lower than the ACS ones, however, the trend is nearly identical. It can be seen in Table C.1 that on average, divorced males and females in the ACS are slightly older than those who I can record in the CPS. However, the proportion who are of high education type is marginally higher in the CPS relative to the ACS. Overall, however, these groups don't appear to be too dissimilar.

	n	Mean age	Prop. H type
CPS males	8046	32.21	0.24
ACS males	54508	32.79	0.21
CPS females	8046	30.85	0.30
ACS females	68770	32.25	0.28

Table C.1: Comparison of attributes for divorced individuals

C.3 Smoothed v. unadjusted dissolution rates



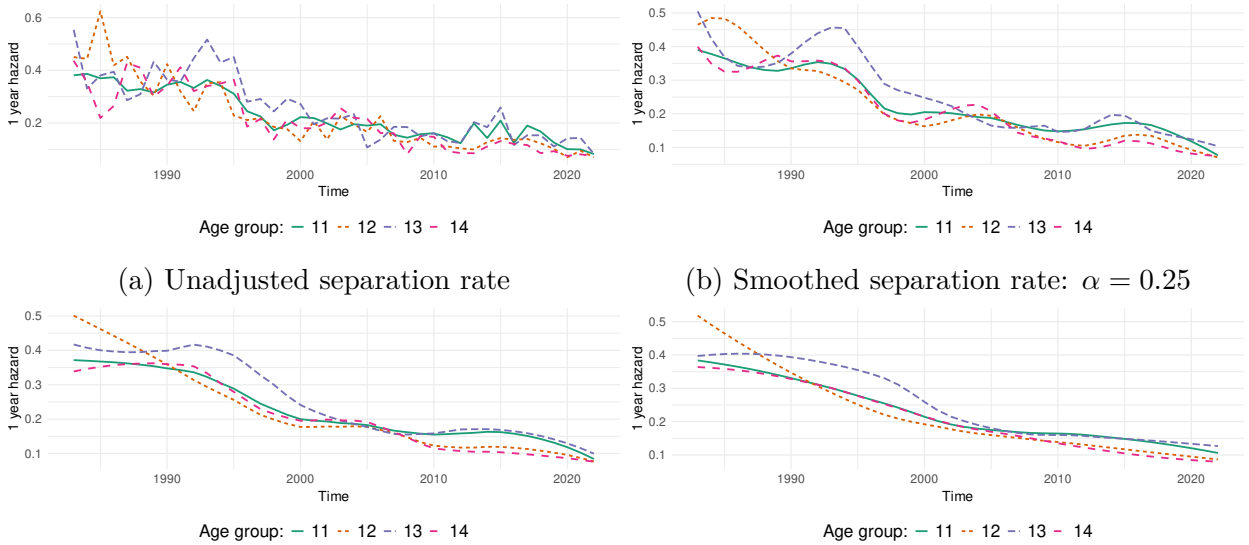
(a) Unadjusted divorce rate

(b) Smoothed divorce rate: $\alpha = 0.25$

(c) Smoothed divorce rate: $\alpha = 0.5$

(d) Smoothed divorce rate: $\alpha = 0.75$

Figure C.14: Illustration of divorce rate smoothing procedure (LOESS).



(a) Unadjusted separation rate

(b) Smoothed separation rate: $\alpha = 0.25$

(c) Smoothed separation rate: $\alpha = 0.50$

(d) Smoothed separation rate: $\alpha = 0.75$

Figure C.15: Illustration of separation rate smoothing procedure (LOESS).

Despite the fact that I have a large number of observations, match dissolutions over a one-year horizon are still quite rare, particularly once you consider many different match types. To address this I apply a locally estimated scatterplot smoothing (LOESS) procedure to the time series of dissolution rates. In Figures C.14 and C.15 I show the smoothed series for different values of α, which is a parameter that controls the rate of smoothing. As α grows, the size of the neighbourhood of points for each local regression grows which results in a smoother curve. For the purposes of estimation in Section 3.7 I chose $\alpha = 0.5$ as some of the noise is removed yet there is still a sufficient amount of shape to give us an idea of the year-to-year fluctuations in the dissolution rates. It should be noted that only the estimation of the expected match value $\overline{V}_t^r(x, y)$ is sensitive to changes in how these rates are smoothed and even then, as long as the general trend is maintained, the conclusions drawn by the model remain the same.

D Policy changes in the 1990s

In this section I'll briefly outline some notable policy changes that occurred in the 1990s.[23]

[23]See Rossin-Slater (2017) for a more detailed explanation of these changes.

D.1 In-hospital voluntary paternity acknowledgement program (IHVPA)

Introduced as part of the Omnibus Budget Reconciliation Act of 1993 (OBRA '93) which aimed to reduce the federal budget deficit through increased tax rates on high-income individuals, changes to Medicare and Medicaid, and IHVPA. The IHVPA allowed unmarried parents to establish legal paternity for their child at birth while still in the hospital. This ties into budget cuts because it could shift the burden of childcare costs from social security programs to unmarried fathers. Prior to this, paternity establishment was a lengthy process that involved a DNA test and often the court system. Once paternity is established, this grants legal rights and responsibility to the father including obligation to provide financial and medical support. This program was strengthened in 1996 with the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) which tied funding to hospitals having a voluntary paternity acknowledgement program. By 1997, nearly all states had implemented IHVPA but there is variation in timing of implementation with most starting around 1994/95.

For a couple to be eligible, the mother had to be legally unmarried at the time of the childbirth. Both parents had to voluntarily agree to sign the acknowledgement form. Of course, some fathers may be unmotivated to sign such an agreement. To try to address this, part of the 1996 reform to this program contained guidance where hospital staff were told to focus on trying to get parents to sign during the time immediately after childbirth—a so-called "happy hour". The thought being that, if the couple were approached during this period, a father may be more willing to commit. It is also worth noting that even if the form was not signed at the hospital, it could still be done later by going to say the Vital Records Office or another relevant government office.

D.2 Personal Responsibility and Work Opportunity Reconciliation Act

There was also a push by the Clinton administration in the mid 1990s to reduce the welfare burden on the United States. This was done through a series of reforms targeting unemployment and child-care benefits. Since these happened at the same time as the roll-out of IHVPA, it is hard to disentangle the effects as they both had implications for how households make decisions. In particular, PRWORA tried to promote marriage and family stability through a few key provisions. States were encouraged to reduce out-of-wedlock births, without raising abortion rates—a $100 million "illegitimacy bonus" was to be awarded to any state which successfully did so. Also, prior to the signing of PRWORA, two-parent families

typically received fewer childcare benefits relative to single-parent families. This has the perverse effect of disincentivizing marriage as in some cases it was financially advantageous for parents to remain unmarried. Single parenthood was also discouraged through stricter rules on timing of benefits. As a result of PRWORA, single parents were required to return to work within two years of the time that the started to receive benefits. Furthermore, states could use what is known as Temporary Assistance for Needy Families (TANF) funds to promote marriage through counseling for couples, relationship skills workshops, and public advertising campaigns encouraging marriage.

D.3 Competing mechanisms

While these two pieces of legislation both had the same goal in that they were introduced to reduce the strain of welfare on the US federal budget, one could propose competing arguments for how these policies might have impacted household formation behaviour. While the purpose of PRWORA was ostensibly to promote marriage, the policy—in its aims to reduce single parenthood—in many ways did not discriminate between marriage and non-marital cohabitation. As such, empirically, it is unclear ex ante exactly which form of coresidential arrangement would increase in frequency. Bitler et al. (2004) show that PRWORA had a negative impact on the number of new marriages and Lundberg and Pollak (2007) suggest something similar. However, likely due to the paucity of information on non-marital cohabitation until relatively recently, the impacts of PRWORA on it are less well-known. Moffitt et al. (2020) find no effect on household formation as a result of welfare reforms but they use a sample which has the typical issues known with measuring cohabitation. In contrast, Ortigueira and Siassi (2022) find that welfare reforms, not PRWORA in particular but a more recent reform for which we have reliable cohabitation data, does indeed have distortionary effects on household formation. They find that anti-poverty programs incentivize cohabitation over marriage.

E Additional information regarding Section 5.3

E.1 Sample construction

Data on homeownership comes from the March Annual Social & Economic Supplement (ASEC) to the CPS. Using IPUMS provided linking information, I can link the ASEC to the main CPS sample. HPI data comes from the US Federal Housing Finance Agency (FHFA) which provides data only for 100 selected—i.e., the largest—metropolitan areas in the US. As such, my sample consists only of those who live in one of these metro areas and also

appears in the March ASEC data. In some cases, the FIPS codes between the CPS and the FHFA do not match exactly and in this case I instead match based on regional proximity. For example, Gary, IN appears in the FHFA data but the closest geographical match in the CPS is to Michigan City–La Porte, IN. The two other cases of this occur where I match Lake County/Kenosha County, WI to Racine WI and Chester County, PA to Reading, PA. Given that these are small areas population-wise, it is unlikely this has any meaningful effect on the results.

E.2 Rent control as an instrument

To perform counterfactual analyses of the impact of home prices on match formation and dissolution, I need to be able to link these prices to the behavioural objects in the model. I do this by regressing these model quantities on home prices. However, there are several reasons why it is possible that OLS is biased and inconsistent in this scenario. Economic conditions which impact home prices also likely impact household formation and it isn't necessarily the case that I am able to control for this using city and time fixed effects. Another concern is reverse causality. Household formation and dissolution can impact housing demand and influence prices. To account for this I use an instrumental variables strategy where I take advantage of the fact that there is variation in rent control policies across cities over my sample period. The identification assumption is that rent control only affects household formation and dissolution through home prices and not directly. There is a possible concern that rent control impacts supply which may affect homeowners and non-homeowners separately. I argue that this is unlikely to be the case in Section E.4.

Of the 100 metropolitan areas in my sample, 18 either had rent control policies in place at the beginning of my sample period (2010) or enacted them at some point during the period 2010–2023. This is summarized in Table E.2. While only 18/100 metro areas have rent control policies, these comprise most of the largest cities in the US. In fact, these cities comprise approximately 30% of the US urban population suggesting there is meaningful variation in my instrument across the sample.

City/Metro	Year Enacted
Anaheim, CA	2019
Bakersfield, CA	2019
Camden, NJ	<2010
Fresno, CA	2019
Los Angeles, CA	<2010
Minneapolis, MN	2021
Nassau County, NY	<2010
New York, NY	<2010
Newark, NJ	<2010
Oxnard, CA	2022
Portland, OR	2019
Riverside, CA	2019
Sacramento, CA	2019
San Diego, CA	2019
San Francisco, CA	<2010
San Jose, CA	<2010
Stockton, CA	2019
Washington, DC	<2010

Table E.2: Summary of rent control timing

E.3 Regression tables

Tables E.3, E.4, and E.5 show the results from estimating the model specification given in Section 5.3. In each case, I estimate three versions of the model. First, without controls, then with added fixed effects and individual-level controls, and finally the IV specification. In the IV specification, the regressions lack power implying the standard errors are rather large—this is currently being addressed and will be fixed in a future version of the paper. However, the coefficients are practically meaningful and directionally consistent with expectations. In each case, the dependent variable is taken in logs and I use a one period lag of the log of HPI as the measure of home prices. As such, the coefficients can be interpreted as elasticities.

Table E.3: Lagged HPI and Interaction Effects (Surplus vs Cost)

	$\overline{V}^M_{ijct}(x,y)$ Surplus			$w^M_{ijct}(x,y)$ Cost		
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged HPI	0.0058	-0.0249		0.0138	-0.0692	
	(0.0144)	(0.0051)		(0.0089)	(20,431.3)	
Lagged HPI (IV)			0.1295			0.4072
			(0.1230)			(0.3434)
Lagged HPI Œ EDUC=LH (IV)			-0.0193			-0.1887
			(0.0375)			(0.1935)
Lagged HPI Œ EDUC=HL (IV)			0.0168			-0.1763
			(0.0723)			(0.1631)
Lagged HPI Œ EDUC=HH (IV)			0.0041			-0.2322
			(0.0474)			(0.1555)
Observations	214,852	214,852	214,852	11,492	11,492	11,492
R^2	0.00010	0.72053	0.70865	0.00056	0.48043	0.39318
Within R^2		0.00394	-0.03838		0.00193	-0.16567
Year fixed effects		✓	✓		✓	✓
City fixed effects		✓	✓		✓	✓
Type fixed effects		✓	✓		✓	✓

SEs clustered at the city level.

Table E.4: Cohabitation: Lagged HPI and Interaction Effects

	$\overline{V}^{C}_{ijct}(x,y)$ Surplus			$w^{C}_{ijct}(x,y)$ Cost		
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged HPI	0.0976***	0.0247**		-0.0493***	-0.0323	
	(0.0277)	(0.0118)		(0.0185)	(0.0249)	
Lagged HPI (IV)			0.2155			-0.0305
			(0.2791)			(1.087)
Lagged HPI Œ EDUC=LH (IV)			0.1468			-0.2887
			(0.2265)			(0.3092)
Lagged HPI Œ EDUC=HL (IV)			0.0269			0.3476
			(0.5882)			(1.504)
Lagged HPI Œ EDUC=HH (IV)			0.0674			-0.0045
			(0.1987)			(0.2723)
Observations	27,468	27,468	27,468	4,875	4,875	4,875
R^2	0.01347	0.66518	0.63707	0.00529	0.45455	0.39091
Within R^2		0.00047	-0.08343		0.00087	-0.11570
Year fixed effects		✓	✓		✓	✓
City fixed effects		✓	✓		✓	✓
Type fixed effects		✓	✓		✓	✓

SEs clustered at the city level.

Table E.5: CohabitationMarriage Switching Cost: Lagged HPI and Interactions

	$w_{ijct}^{C\|M}(x,y)$		
	(1)	(2)	(3)
Lagged HPI	0.1509	0.0046	
	(0.0156)	(0.0182)	
Lagged HPI (IV)			0.1190
			(0.2848)
Lagged HPI Œ EDUC=LH (IV)			0.2421
			(0.3184)
Lagged HPI Œ EDUC=HL (IV)			0.1063
			(0.3254)
Lagged HPI Œ EDUC=HH (IV)			0.2695
			(0.2294)
Observations	29,217	29,217	29,217
R^2	0.02219	0.31673	0.29281
Within R^2		5.34×10^{-6}	-0.03501
Year fixed effects		✓	✓
City fixed effects		✓	✓
Type fixed effects		✓	✓

SEs clustered at the city level.

E.4 Robustness

One potential threat to identification is that rent control policies are not truly exogenous because they impact homeowners and non-homeowners separately. Given that homeownership is relevant for match formation and dissolution, this opens up a potential channel by which the exclusion restriction is violated. To account for this, I control for homeownership in a simple IV regression—i.e., without the interaction terms. The coefficient estimates shown in Table E.6 aren't directly comparable to those presented in Tables E.3 and E.4 due to the fact that these are different samples of individuals. Homeownership is not something which is observable for all households in the CPS. It is only for those which I can link to the March ASEC supplement. However, in any case, what is of interest is if the coefficient on HPI changes once homeownership is controlled for. In the case of surplus, the estimates do not

change. For cost, there is a slight change but in both cases the effect is small and positive.

Table E.6: Lagged HPI (IV) Surplus and Cost, HO Sample vs Control

	$\overline{V}^{C}_{ijct}(x,y)$ Surplus		$w^{C}_{ijct}(x,y)$ Cost	
	(1)	(2)	(3)	(4)
Lagged HPI (IV)	0.3296	0.3269	0.0415	0.0270
	(0.2825)	(0.2839)	(0.4142)	(0.4329)
Observations	51,235	51,235	2,628	2,628
R^2	0.67061	0.67256	0.50660	0.50872
Adjusted R^2	0.66988	0.67183	0.48463	0.48664
Control for HOMEOWNER		Yes		Yes

SEs clustered at the city level.